Process-Driven Input Profiling for Plastics Processing

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Most plastic processing set points are variables that need to be defined for each sample point of the cycle. However, in the absence of on-line measures of part quality, the set points cannot be defined by feedback and need to be prescribed a priori for the entire cycle. In conventional practice, the shape of each set-point profile is defined either heuristically, according to qualitative experience, or mechanistically, to enforce a predefined trajectory for a simulated internal process state that is used as a surrogate measure of part quality (e.g., the velocity profile defined to dictate a constant melt front velocity). The purpose of this study is twofold: (i) to evaluate the efficacy of using a single internal state as the surrogate of part quality, and (ii) to explore the feasibility of devising a multivariate profiling approach, where indices of multiple process states act as surrogates of part quality. For this study, an injection-compression molding process used for production of digital video disks was considered as the development domain, and a pseudo-optimal cycle of the process was found by reinforcement learning to provide a basis for evaluating the ideal behavior of the process states. Compared to conventional molding, the results indicate that the asymmetric process capability index, CPK, was increased by ∼50% with velocity profile optimization and to 120% with both velocity profile and pressure profile optimization. Two general conclusions result. First, velocity and pressure profiling provide important degrees of freedom for optimizing process control and maximizing part quality. Second, estimators for unobservable process states, in this case birefringence and warpage, can be used to develop different machine profiles to selectively trade off multiple quality attributes according to user preferences. [DOI: 10.1115/1.2738094]

1 Introduction

Process control has been recognized as an important means of improving the performance and consistency of thermoplastic parts. However, control of polymer processing is significantly challenged by the nonlinear behavior of the polymeric materials, dynamic and coupled process physics, and convoluted interactions between the mold geometry and final product quality attributes [1]. The different levels of control in polymer processing are shown in Fig. 1. At the innermost level, only the machine actuators are regulated to ensure proper execution of the programed machine set points. At the second level, the inputs may be actively controlled to force internal (state) variables, such as melt temperature and melt pressure, to follow prespecified trajectories [2–5]. Although this level of control is the most desirable for its precise control of the melt flow, it is hindered by (and rarely used due to) the absence of sensory information about the state variables as well as our ignorance of the trajectories they need to follow. At the outermost level, the nominal levels of machine set points are adjusted so as to improve the quality of the part through better set points [6–13].

Every stage of injection molding has set points and profiles that need to be determined. A primary difficulty in specifying the set-point profiles is that performance feedback based on quality measures does not become available until the part is produced. Instrumentation does not yet exist, and may never exist, to directly measure the aesthetics or structural integrity prior to opening of the mold and inspection of the ejected part. This lack of observability precludes assessment of the effect of individual segments of the profile on the quality of the part; thus, set-point profiles have been traditionally determined off line by trial-and-error or mechanistically via process simulation. The trial-and-error approach could be time consuming and dependent on the skill and luck of the operator, but does not require process simulation. The mechanistic approach, on the other hand, assumes knowledge of the ideal behavior of an individual internal state variable and defines the set-point profile so as to enforce that behavior. For example, a common set-point profiling practice used in industry is to specify the ram velocity profile such that a uniform melt front velocity is achieved during the filling of the cavity. A mold-filling simulation is performed to simulate the distributed melt front velocity, from which the ram velocity profile is computed to enforce a predetermined average velocity at the melt front throughout the mold-filling process. Although such an approach has been implemented in commercial simulation with reasonable success [14–16], it is disadvantaged by its univariate approach, which ignores the effect of other state variables on the part quality and imposes conditions on them that may not be optimal.

The present study was conducted on an injection-compression molding process used for production of digital video disks, compact disks, and rewritable compact disks. The simulation program for this process is based on the axisymmetric modeling of nonisothermal, non-Newtonian flow of the polymer melt and allows arbitrary specification of boundary and initial conditions [17,18]. Specifically, the simulation solves the pressure, flow rate, and temperature fields at different time steps and melt front positions. The simulation assumes laminar creeping flow with a no slip condition at the mold wall, thermal contact resistance between the polymer melt and the mold wall modeled as convective heat transfer, and prescribed boundary conditions for inlet flow rate, melt pressure, melt temperature, and clamp force. For the modeling of the flow and thermally induced stresses, a nonlinear viscoelastic constitutive equation is adopted. The simulation also includes nonlinear buckling (structural finite element) analysis with gravity effects for modeling of post-molding disk deformation, as well as several other constitutive models for predicting other quality attributes.

In molding of the CD_R and DVD substrates, two of the most important part quality attributes are birefringence and warpage. Birefringence is the refraction of light, as it passes through a

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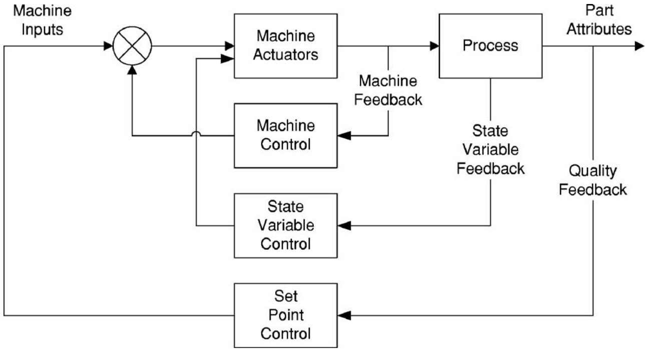

Fig. 1 Schematic of injection molding control

material, into two different components due to different refractive indices of the material. Birefringence can reduce the signal-to-noise ratio in the player by causing optical aberration of the reader spot. Warpage is caused by internal residual stresses and reduces the dimensional stability of the disks. For DVDs, warpage is particularly detrimental because it hinders the bonding of multiple substrates and induces additional in-plane birefringence [18]. It is therefore desirable to reduce both birefringence and warpage by controlling the process set points. Along with simulated birefringence and warpage values, simulated values of key state variables, such as bulk temperature, cavity pressure, flow rate, maximum shear rate, and maximum shear stress, were recorded at different locations of the mold and during different stages of the cycle to provide the database for deriving the quality indices.

With regard to the state of the art in optical media molding, there are at least three, and potentially five, set-point profiles that need to be defined. These include the velocity profile as a function of ram position to control the progression of the melt front during cavity filling, the packing pressure as a function of time to control the magnitude of pressure in the cavity during solidification, and the clamp tonnage as a function of time to control the distribution of pressure in the cavity. The mold and melt temperature profiles may also be controlled in the future, though this is beyond the current state of the art in machine design.

The objective of the present study is to investigate the validity of the univariate approach and explore the feasibility of a multivariate approach, wherein multiple state variables are used as surrogates of part quality. To investigate the validity of the univariate approach, a pseudo-optimal cycle was found empirically by reinforcement learning to provide a reference "ideal" cycle. An analysis of the state variables that were most markedly related to the part quality attributes revealed that no single variable was the dominant factor of part quality during the entire cycle. To evaluate the feasibility of a multivariate profiling approach, surrogate models (indices) of part quality were formed in terms of the most effective internal variables. These surrogate indices were then used by a sequential programing (SP) method that progressively constructed the segments of the profiles. The digital video disks produced from the experimental evaluation of the generated profiles were observed to have better quality values with the multivariate profiling approach.

2 An Ideal Cycle

The first task of this research is to evaluate the validity of the univariate mechanistic approach to profiling. For this, we need to determine if any single internal variable can be used as a surrogate measure of part quality for the entire cycle. If such an internal variable is found, it can then be used as an in-process feedback measure, albeit in simulation, to guide the profiling. However, given the high correlation between the internal states and set points, such a study of internal states cannot be performed under arbitrary process conditions and needs to be confined to the operating conditions prevalent during a desirable cycle. It is speculated here that the most desirable cycle is an "optimal cycle" that produces a part with the best quality attributes. For this application, the ideal cycle would have minimum cycle time and zero birefringence and warpage, but given that such an ideal cycle cannot exist, the process engineer must practically trade off cycle-time, birefringence, and warpage relative to specifications. This task is made difficult since birefringence and warpage are not measurable in situ and can be only measured after a significant process delay.

Accordingly, the search for the optimal cycle in injection molding is hampered by the absence of immediate feedback at individual time steps. A possible approach to the search for the optimal cycle is reinforcement learning using Monte Carlo sampling methods [20,21]. Reinforcement learning using Monte Carlo methods only requires "experience" from on-line observations or simulation models of the injection molding process, without explicit models of the process dynamics or complete knowledge of all possible states. The principle advantage of reinforcement learning methods is that they learn the value function through on-line exploration, so unlike dynamic programing, which develops the value function for the entire space off line, they operate only on parts of the state space that are relevant to the process. More importantly, reinforcement learning allows the use of "episodic" information, which in the case of injection molding would be the part quality estimates at the end of a complete cycle, instead of requiring feedback at each time step within a cycle. These advantages and the ability to handle high degrees of nonlinearity and uncertainty in the process make the reinforcement learning approach better suited to this problem than traditional mathematical programing methods [19,20].

In reinforcement learning terminology, decisions are made while interacting with the environment (process), based on the "state" of the system and the expected "reward" from taking the action. Therefore, the injection molding cycle needs to be represented by a sequence of states, which can be characterized by the internal state variables, such as melt pressure, melt temperature, flow rate, etc. The reward in this process is a function of the final part quality characteristics, such as geometrical measures, surface characteristics, strength, and the manufacturing rate. The actions represent the values of the input profiles at a particular point in the injection molding cycle. The goal is to select actions for each process state such that the total reward over the long run from the environment is maximized. Sometimes it is possible to assign instant rewards to individual actions to incorporate a bias in selection of actions (e.g., to credit higher ram velocity values for reduced cycle times), but the final reward that represents the effect of the profile on the part quality is only known at the end of the cycle.

Briefly, reinforcement learning relies on the estimation of an action value function [19]

$$\mathbf{Q}^{\pi}(s,a) = E_{\pi}\{R_t | s_t = s, a_t = a\} \tag{1}$$

which assesses the action value through the reward function R_t of action a at the current time t when the system is in state s. The policy π, in the case of injection molding, defines the set-point profiles. Virtually, all of the methods developed to find the optimal policy (control schedule) for delayed reward problems rely on an estimation of the value function. In Monte Carlo methods, various sets of state-action pairs are explored in episodes and evaluated by their final return. An "action value matrix" $\mathbf{Q}(s,a) \in \Re^{n\times m}$ is used to represent the average return of every possible state-action pair, where n denotes the number of states and m the number of available actions. As such, after each episode, the action value matrix $\mathbf{Q}$ is updated to include the average returns of those state-action pairs just explored. The average returns included in the updated action value matrix provide the basis for selection of new actions for individual states in the next episode. In the ϵ-greedy method [20], which will be investigated in the proposed research, the state-action pairs with the highest average return in $\mathbf{Q}$ are selected with the probability of $1-\epsilon$ for the next episode, while the chance of selecting all other state-action pairs at random, uniformly and independently of the action-value estimates, is given a probability of ϵ ($\epsilon \in [0.1\ 0.3]$). As such, the smaller values of ϵ result in lower probabilities of exploration for lower reward state-action pairs. Given that the action value matrix is initially a null matrix and any unexplored state-action pair has a corresponding zero average return in this matrix, a smaller ϵ value would reduce the tendency to try new state-action pairs. Therefore, smaller ϵ values reduce the level of exploration and increase the possibility of entrapment in a local minimum. Conversely, larger ϵ values increase the chance of finding the optimal solution at the expense of more explorations. Hence, selection of ϵ is an important consideration in this approach. Once the parameters have been determined for the search, the Monte Carlo method asymptotically gives

$$\arg\max_a Q(s_i,a_j) \rightarrow a^*(s) \tag{2}$$

where $a^*(s)$ denotes the optimum action for state s_i. It is important to note that the optimum action set and the reward function may have many-to-one relationships, wherein several combinations of actions result in the same final reward.

For the present study, the velocity and pressure profiles were adapted one at a time. First, the velocity profile was adapted, with the packing pressure profile unchanged during adaptation. Then the packing pressure profile was adapted, with the velocity profile at its best setting.

Posed as an optimization problem, the objective was to provide the shortest cycle that would produce parts with the best combination of birefringence and warpage values. To frame the problem for reinforcement learning, the total length of the melt front $S_{\max}$, which is dictated by the mold geometry, was divided into separate intervals of ram position to denote the individual states of the process. The injection-compression machine that was used for the experimental phase of this study had a ram position range of 31.5–3.5 mm in the injection stage. This range was divided into ten positions to denote the states of the cycle. In velocity profiling, the action set was defined as $a_j^T=\{0.2V_{\max},0.3V_{\max},\ldots,V_{\max}\}^T$, where $V_{\max}$ denotes the maximum ram velocity. The velocity values ranged from 30 mm/s to 150 mm/s. Analytically, for the states defined as s_i; $i=0,\ldots,n$ and the actions as a_j; $j=0,\ldots,m$ the task of velocity adaptation was to continually seek sets of state-action pairs that would reduce the cycle time while improving the part quality.

The reward mechanism for the adaptation process comprised two components. In order to give preference to shorter cycle times, larger rewards were assigned to higher velocity values by the instant reward mechanism

$$r_j(a_j) = k_1 v_j \tag{3}$$

where k_1 denotes the weight of reward associated with cycle time. The end rewards associated with the part quality measures were defined as

$$r_{\text{end}} = k_2(B_0 - B) + k_3(W_0 - W) \tag{4}$$

where B and W denote the maximum birefringence and warpage values along the radii of the simulated part in each episode, and B_0 and W_0 represent their initial values from the previous episode. The above value function (Eq. (4)) indicates that if the simulated birefringence B is smaller than its initial value, then a positive reward proportional to the improvement is assigned to the selected actions; otherwise, a negative reward is assigned. The coefficients k_2 and k_3 represent the relative significance of the two quality measures in the reward function. Since, in the production of DVDs, the injection stage comprises a small portion of the cycle time (~3%), cycle time cannot be substantially reduced by the injection velocity. The reward associated with higher velocity values is therefore assigned a smaller weight (i.e., $k_1=0.01$) than those associated with the optical quality measures ($k_2=1$ and $k_3=0.4$). According to the above reward mechanism, the return R_t of each state-action pair was computed as

$$R_t(s_i,a_j) = \sum_{k=i+1}^{n} r(s_k,a_j) + r_{\text{end}} \tag{5}$$

In practice, the injection velocity profile consists of low values at the beginning of the cycle followed by high values to reduce cycle time and to avoid short shots. The velocity is reduced toward the end of the cycle to avoid overpacking. This practice was enforced by establishing lower and upper bounds on the actions to be selected at each state. Another potential constraint on adaptation of the velocity profile is imposed by the actuator dynamic response. In order to account for actuator dynamics, an acceleration constraint was imposed on the possible actions to be considered at each step.

The adaptation strategy was implemented in simulation. Velocity adaptation started with an initial velocity profile. After each adaptation episode, the total reward of each state-action pair was computed based on the instant reward of individual velocity value and the end reward from the birefringence and warpage values generated by the simulation (Eq. (5)). The $\mathbf{Q}^\pi$ matrix was then updated by averaging the accumulated return. The new input profile for the next run of the simulation program was selected based on the $\mathbf{Q}^\pi$ matrix. A major concern in reinforcement learning is the large number of iterations needed, which may be prohibitively time consuming in long simulations. In this simulation program, the disk was treated as a series of one-dimensional strips of incremental width represented by finite elements [18]. It has been determined experimentally that representation of the disk by 40 elements provides adequate precision, but it takes over 20 min to run on a modern PC. Here, in order to expedite the adaptation process, only 20 elements were used in simulation, although the final results were verified with 40 elements in simulation.

Packing pressure adaptation was performed similar to velocity adaptation. According to experience, the melt solidifies in ~1 s, after which only low back pressure is needed. Therefore, adaptation only dealt with the pressure during the first 1.2 s of the cycle and was set to the constant value of 1 kgf/cm^2 thereafter. To define the states, the packing time of 0–1.2 s was divided into six intervals, and the beginning of each interval was used as a state. The action values were defined according to the machine capability as 13 discrete packing pressure values in the range of 2.5–30 kgf/cm^2. Packing pressure can be changed rapidly; thus no dynamic constraints were necessary during adaptation, and since cycle time is not affected by packing pressure, no instant reward mechanism could be defined to bias action selection. The end reward associated with each pressure profile was defined similar to the one for velocity adaptation. The objective function and weighting coefficients used here are to demonstrate the concept; otherwise, the development of objective functions and appropriate weighting coefficients that reflect the decision maker's true preferences is an ongoing activity [21–23].

Profile adaptation studies performed with different initial profiles resulted in mostly identical final profiles, indicating the robustness of the adaptation routine to the starting profiles. The improvement in the part quality attributes attained by velocity adaptation is reflected in the maximum birefringence and warpage values shown in Fig. 2. The results indicate that birefringence was reduced from an initial value of 137 nm, for the initial profile, to 110 nm by the final profile, and that the maximum warpage was reduced from 98.20 μm to 97.1 μm. The relatively low improvement in warpage is due to the smaller weight in the value function (1.0 for birefringence and 0.4 for warpage).

3 Surrogate Measures of Part Quality

From the near-optimal profiles obtained for the velocity, packing pressure, and clamp tonnage, the desirable operating conditions for the internal states can be simulated. The internal states

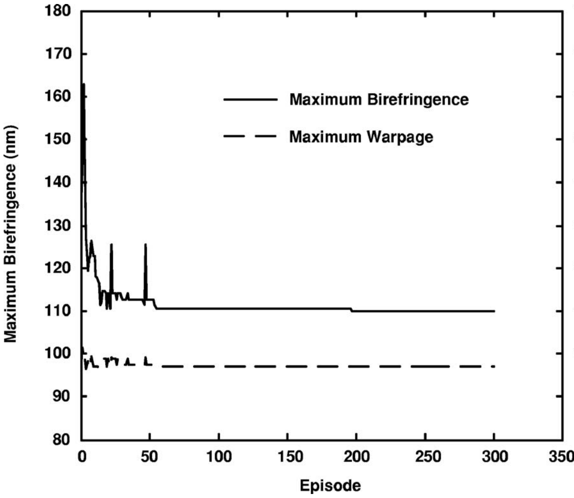

Fig. 2 Simulated values of birefringence and warpage during the adaptation of the velocity profile by reinforcement learning

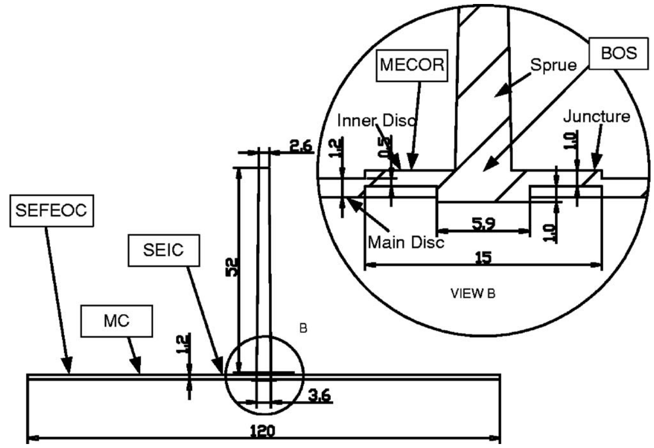

Fig. 3 Location of the recorded internal states within the mold cavity and sprue of CD-R

recorded are listed in Table 1. Their simulated values were recorded for the following five locations: BOS: Bottom of sprue, MECOR: Middle element cutoff ring, SEIC: Second element in cavity, MC: Middle cavity, SEFEOC: Second element from end of cavity, as shown in Fig. 3. The contribution of each state variable to the simulated birefringence and warpage was first studied through correlation analysis. The correlation coefficients varied as functions of time, reflecting the varying effects of internal states on the part quality during different stages of the process. For instance, it was observed that the coefficients for all the variables were quite small at the beginning of the cycle, reflecting their expected low influence on part quality in the early stages of the cycle. The flow rate, for example, is expected to have an influence on part quality during the filling phase, but it cannot affect the part quality during the packing stage when the gate is frozen and the melt cannot flow into the cavity. This time-dependent nature of the correlation coefficients indicates the temporal significance of internal states during the different stages of the cycle and supports the hypothesis that no single variable alone can be an effective surrogate of part quality throughout the cycle. This, in turn, implies that a univariate profiling approach cannot be as effective as a multivariate one.

Cross-correlation analysis offers a mechanism to identify the overlap between the state variables. Based on the cross-correlation values, the state variables were divided into three groups, as shown in Table 1, and one state variable from each group was selected based on the consistency and magnitude of its correlation coefficient with respect to the quality attributes. The bulk temperature v_1 was selected from group 1 (G_1), thickness v_4 from group 2 (G_2), and flow rate v_3 from group 3 (G_3). The significance of the state variables v_1, v_4, and v_3 at each time step within the cycle were evaluated next by R^2 regression [24]. Briefly, linear regressions of the form

$$\hat{B} \text{ or } \hat{W} = a_0 + a_1(t)v_1(t) + a_3(t)v_3(t) + a_4(t)v_4(t)$$

were performed with different combinations of state variables at each time step and the fits provided were evaluated according to the R^2 measure [24]. The state variables included in the linear regression model with the highest R^2 value were then defined as significant at that time step. In cases where the R^2 values were close for several models, the model with the fewer state variables was selected. The quality indices were then defined in the time spans that the same internal states were significant. The empirical quality indices defined here satisfy the purpose of the present study, which is to investigate the merit of a multivariate mechanistic profiling approach, but they lack generality. A desirable outcome of this research would have been the identification of single internal states that would be effective surrogates of part-quality for distinct segments of the cycle. Since the results did not support such an outcome, we were forced to define our part-quality surrogates in terms of regression models to be able to continue our study toward evaluating the proposed profiling approach. It should be noted, however, that for the proposed multivariate profiling to be broadly applicable, more fundamental and generic quality indices will be needed.

Table 1 The internal state variables simulated at different locations within the mold.

Internal states	Grouping
$\boldsymbol{v}_1$: Bulk temperature (C)	G_1
$\boldsymbol{v}_2$: Pressure (bar)	G_1
$\boldsymbol{v}_3$: Flow rate (cc/s)	G_3
$\boldsymbol{v}_4$: Thickness (mm)	G_2
$\boldsymbol{v}_5$: Max shear rate (1/s)	G_3
$\boldsymbol{v}_6$: Max temperature difference in z direction (C)	G_1
$\boldsymbol{v}_7$: Max normal stress difference (MPa)	G_2
$\boldsymbol{v}_8$: Max density difference (g/cc)	G_1
$\boldsymbol{v}_9$: Max shear stress (MPa)	G_2

4 Multivariate Profiling

With the simulated value functions defined in terms of internal process states, the profiling problem converts to an optimization problem that can be ideally solved by dynamic programing [25]. However, dynamic programing requires all profile combinations to be evaluated, which is impractical for problems with time-consuming simulation. For instance, a set point profile consisting of n segments and m possible levels per set point requires a total of m^n simulation runs. For average profiles with m and n on the order of ten, even a few seconds per each simulation run would translate into months of computation for the solution.

As a compromise to dynamic programing, an incremental approach was adopted here whereby segments of the profiles were progressively constructed according to the simulated value function. The advantage of this method is that it can avoid unnecessary computation by running the simulation program only to the point influenced by the profile segment, but it poses the risk of finding a local optimum. In the implemented method, the values of the first two set-point sequences were determined first by evaluating all possible choices for these two set points, as in dynamic programing. If each point in the profile could take one of m possible

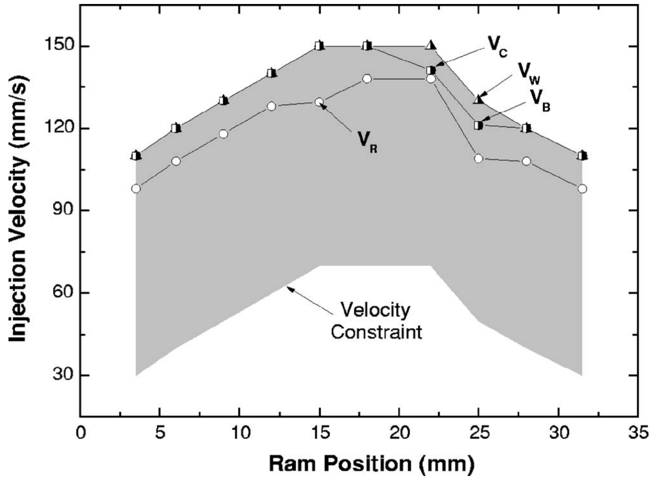

Fig. 4 Velocity profile by sequential programing (SP) to enhance birefringence (V_B), warpage (V_W), and birefringence and warpage together (V_C) compared to the profile from reinforcement learning (V_R)

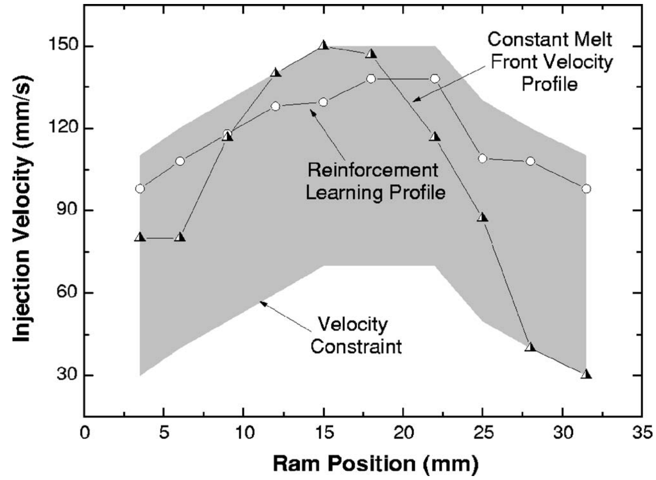

Fig. 5 Velocity profile to maintain a constant melt front velocity compared to the one from reinforcement learning

values, then a total of m^2 simulation runs would be necessary for this two set-point segment. Among the m^2 profile segments evaluated, the segment associated with the lowest/highest value index would be selected. Moving to the next segment, consisting of three set-point sequences, with two of the set points already selected, only m simulation runs were necessary, since there were only m possible new values to be considered for the last set point in the segment. Process simulation would therefore need to be performed m times, one for each of the possible set-point values, again only to the point influenced by the set-point segment. This process would be continued for each new segment of the profile, each requiring m partial simulation runs until the last set point in the sequence was determined. Accordingly, the described approach required only $m \times (n+m-2)$ partial evaluations to develop a profile consisting of n segments. Just as a set-point segment may be dependent on the other segments, a set-point profile may be dependent on other profiles. In the method described above, the profiles were determined one at a time, so they were generated by also neglecting the potential coupling among them.

For this study, only the velocity and packing pressure set points were profiled. Given that these profiles were defined in separate iterations, the velocity profile was first obtained with the packing pressure at its initial setting, and then the packing pressure profile was defined with the velocity profile set at its newly obtained value.

The velocity profile was first defined according to the quality index representing birefringence (V_B), then according to the one representing warpage (V_W), and finally according to both indices with weights identical to those used in the reinforcement learning solution (1.0 for birefringence and 0.4 for warpage). The three velocity profiles obtained are compared to the profile from reinforcement learning in Fig. 4. The closeness of the profiles in Fig. 4 indicates that the profiling method produces profiles similar to that generated by reinforcement learning, despite its use of state variables in lieu of part quality attributes and its less than thorough search strategy. In addition to these profiles, a velocity profile was generated to maintain the flow front velocity constant, as often practiced in many injection molding applications. This profile, which is compared to the reinforcement learning solution in Fig. 5, is substantially different from the other profiles.

But to evaluate the suitability of the above profiles, one needs to compare the part quality they produce. The simulated values of birefringence and warpage for each of the profiles in Figs. 4 and 5 are shown in Table 2. The first set of quality attributes corresponds to the velocity profile by reinforcement learning (RL), followed by those associated with each of the velocity profiles in Figs. 4 and 5. Since at this stage the packing pressure profile had not been adapted yet, the simulations were run with the initial packing pressure profile P_I.

The packing pressure for the first 1.2 s of the packing stage was determined similar to the velocity profile but was set to a constant thereafter for the duration of the packing stage. As before, the profiles were determined separately according to the indices of birefringence and warpage, and their combination. These profiles are compared to the profile obtained by reinforcement learning in Fig. 6. The profiles to enhance birefringence and warpage are quite similar and somewhat lower than the profile obtained by reinforcement learning. But when these profiles are compared in terms of the quality attributes they produce (see Table 3), they both surpass the one by reinforcement learning. It should be noted, however, that the simulated quality attributes in Table 3 are also affected by the accompanying velocity profile, which is different for each of the four sets of results. The fact that different sets of profiles produce very similar part quality attributes is indicative of their nonunique nature. In practice, maintaining a constant melt front velocity during the cycle is often considered desirable. But as shown in Table 2, the birefringence and warpage values from the constant melt front velocity profiles are noticeably larger than those from reinforcement learning and multivariate profiling.

5 Experimental Validation

Optical media experiments were conducted for all profiles on a Sumitomo SD30 injection-molding machine. All laboratory experimentation was conducted at General Electric Plastics' Polymer

Table 2 The simulated values of birefringence and warpage using the velocity profiles obtained by reinforcement learning and sequential programing (SP). The notations are the same as in Fig. 4, i.e., V_R denotes the velocity profile from reinforcement learning, V_B is the velocity profile by SP to enhance birefringence, V_W enhances warpage, V_C enhances birefringence and warpage together, and P_I represents the initial pressure profile.

RL V_R, P_I		SP with B V_B, P_I		SP with W V_W, P_I		SP with B and W V_C, P_I		Constant melt front V_M, P_I	
B_R	W_R	B_B	W_B	B_W	W_W	B_C	W_C	B_M	W_M
109.9	97.1	96.3	97.5	94.0	97.3	96.3	97.5	159.7	92.6

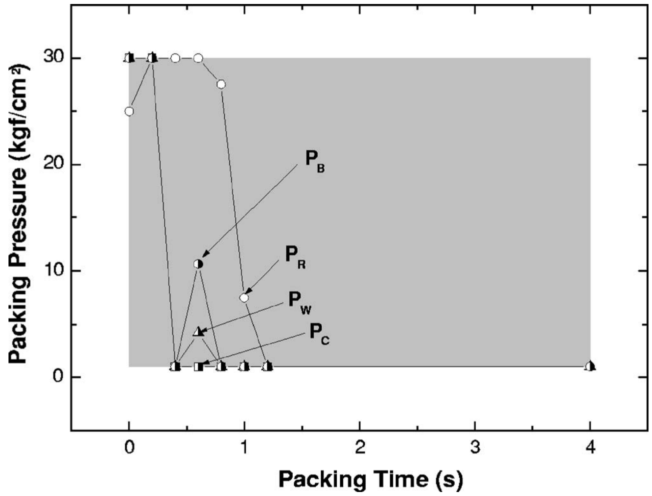

Fig. 6 Pressure profile by SP to enhance P_B, P_W, and P_C with P_R

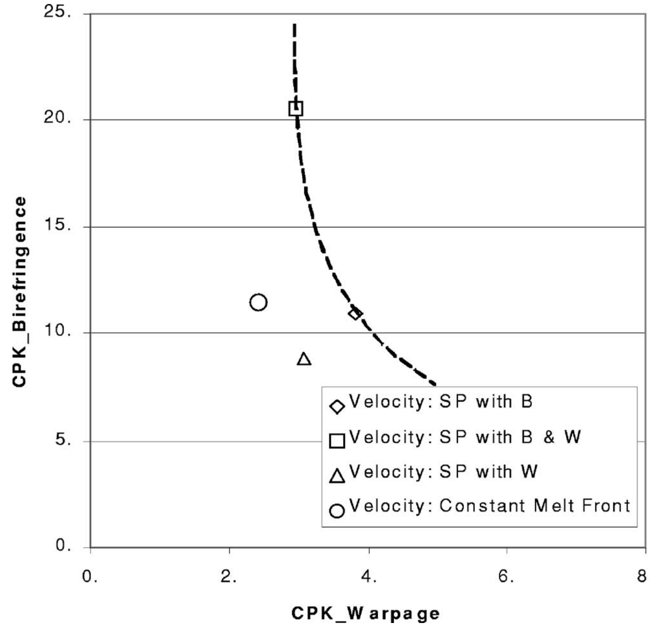

Fig. 7 Process capability of birefringence and warpage for four velocity profiles (SP refers to profiles generated by sequential programing)

Processing Development Center (Pittsfield, MA) in the Optical Media Development Center (OMDC). In the OMDC, the Sumitomo SD30 is configured as a batch process. Technically, the Sumitomo is a 30 ton hydraulic machine with a mechanical clamp, capable of producing quality CD substrates with cycle times of <3 s. The Sumitomo mold is configured with four independent zones of mold cooling, which translates to two independent zones per mold half. The robotic disk take-out arm is quite advanced, using vacuum to secure the disk during removal and small gripping fingers to remove the sprue. In addition, the Sumitomo has an expanded injection compression molding (ICM) control sequence. The Sumitomo uses a clamp pressure profile triggered by timing delays from injection start. Therefore, an initial clamp pressure can be specified followed by up to three different pressure stages at different delay times during molding. In addition, the transition time between stages is controllable, allowing for a clamp pressure ramp profile between stage tonnages.

The injection molding machine was equipped with a data acquisition system to monitor the performance of the molding machine and process. The system acquires molding machine signals generated by the machine's internal process measurement devices, including clamp pressure, melt pressure, melt temperature, ram velocity, shot size, etc. In addition, the machine is instrumented to measure mold displacement, disk temperature, and static level after ejection. Disk handling and testing procedures were uniformly maintained. The entire cross section of the disk may not be below the glass transition temperature T_g; hence, handling must be minimized until cooling is complete. In the laboratory, all disks were handled by a pneumatic robot that secures the disk by means of a vacuum around the center hub. As a standard practice, disks were stacked in batches by robotic means and allowed to cool for 24 h before testing. The substrate testing equipment included an atomic force microscope (Topometrix) and optical disk scanner (Dr. Schenk). After the necessary unsputtered measurements, the substrates were batch processed for sputtering and bonding, and final testing of the sputtered disks was completed with the appropriate player signal analyzers (CD Associates). The performance of the molding process with the various profiles was measured according to the asymmetric process capability index for both birefringence and warpage

$$C_{PK} = \min\left[\frac{\text{USL} - \mu}{3\sigma}, \frac{\mu - \text{LSL}}{3\sigma}\right] \tag{6}$$

where USL and LSL are the upper and lower specification limits, respectively, and μ and σ are the observed average and standard deviation for birefringence and warpage across 15 molded disks. According to Six Sigma guidelines, a process capability of at least two is desired to ensure that six standard deviations lie between the process mean and the closest specification limit. Although process capabilities far beyond two do not significantly reduce the rate of defects, they are indicative of an opportunity for cost reduction through allowable increases in production rates. Alternatively, very high process capabilities indicate the possibility for tightening specifications, which is necessary to achieve high data densities as in the next generation of optical media based on blue lasers. The process capability index for birefringence is plotted in Fig. 7 against the process capability index for warpage for each of the four velocity profiles. It is desirable to maximize both of these quantities. The dashed line indicates an estimate of the pareto-optimal boundary, which represents the trade-off between warpage and birefringence, and beyond which further process capability may not be achievable without other changes in the process. It should be noted that this is only an estimate of the pareto-optimal boundary, since it is economically intractable to exhaustively search the processing space to guarantee optimality given the dimensionality of this manufacturing problem.

There are two interesting observations to be made from Fig. 7: (i) that the conventional profile, based on a constant melt front velocity, is suboptimal, and (ii) the described optimization algorithms are mostly consistent with the observed results, for instance, the profile optimized for warpage provides a higher pro-

Table 3 The simulated values of birefringence and warpage using the velocity and packing pressure profiles obtained by reinforcement learning and SP. The notations are the same as in Figure 4, i.e., V_R (P_R) denotes the velocity (pressure) profile from reinforcement learning, V_B (P_B) is the velocity (pressure) profile by SP to enhance birefringence, V_W (P_W) enhances warpage, and V_C (P_C) enhances birefringence and warpage together.

RL		SP with B		SP with W		SP with B and W	
V_R, P_R		V_B, P_B		V_W, P_W		V_C, P_C	
B_R	W_R	B_B	W_B	B_W	W_W	B_C	W_C
102.6	93.9	92.6	89.0	90.1	88.1	93.5	88.8

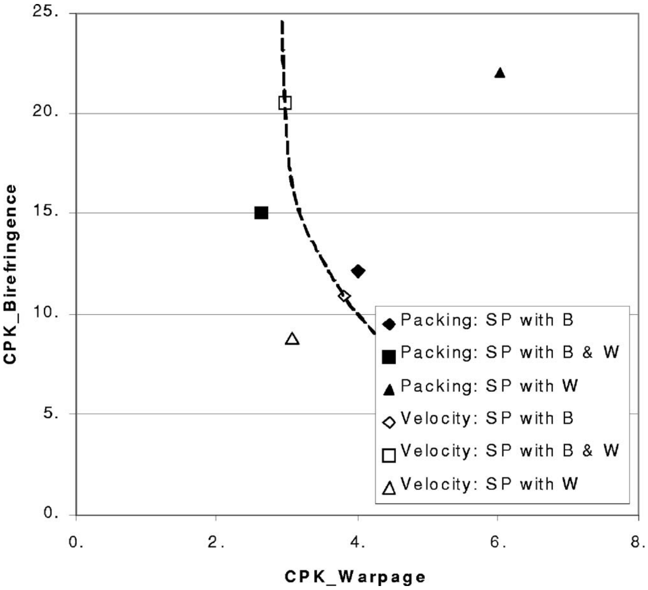

Fig. 8 Process capability of birefringence and warpage for three pressure profiles from sequential programing (SP), along with those for velocity profiles in Fig. 7

cess capability for warpage at the expense of birefringence. The results indicate that it is possible to improve the birefringence and/or warpage without adversely affecting other quality attributes and that the described profiling strategy provides significant process improvements compared to the univariate method. This verifies the hypothesis that the additional degrees of freedom used in the proposed multivariate profiling method improve the controllability of the quality attributes. There are some inconsistencies, too. For example, the profile optimized for warpage is suboptimal and the profile optimized for birefringence has better warpage and poorer birefringence than the profile simultaneously optimized for birefringence and warpage. Part of this inconsistency can be attributed to the inaccuracy of simulation, which was the basis for this profiling study.

Similar to those shown for the velocity profile, the process capability index for birefringence is plotted in Fig. 8 against the process capability index for warpage for each of the three pressure profiles. Each of the pressure profiles was optimized using the velocity profile with the corresponding objective function. For example, the packing pressure profile for optimizing birefringence was generated and validated with the velocity profile generated for optimizing birefringence. For convenience, the results of Fig. 7 are also included in Fig. 8. It should be expected that the process capability indices would be improved given the optimized packing profiles, and this expectation was fulfilled in two of the three cases.

The results indicate that, by and large, multivariate profiling offers significant promise for improving the quality of manufactured parts, especially since the dimensionality of such profiling problems prevents on-line optimization to approach the true pareto-optimal boundary. The discrepancies observed between the simulated and experimental results may have been caused by (i) the suboptimality of the generated profiles due to machine constraints such as maximum ram velocity; (ii) errors between the simulation predictions and physical observations, due (for instance) to inaccurate modeling of heat transfer rates from the hot polymer to the mold and the limited number of finite elements used in simulation for reduced computation; (iii) potential coupling between the velocity and packing pressure profiles; and (iv) indefinite optimality given the dimensionality of the profiling problem. Although the presented results support the hypothesis of the study regarding the promise of multivariate profiling, they point to the need for additional research that can address the above issues and others.

6 Conclusion

Input profiling in plastics processing has been underutilized and is, in fact, fraught with myths in actual practice. As noted earlier, one of the primary challenges to tuning manufacturing processes is the lack of direct control of the product quality attributes. Indeed, many product quality attributes directly conflict with other quality attributes and cycle economics. As such, set-point profiling provides a potentially valuable approach to increasing the controllability of manufacturing processes without any increased investment in process technology, or delays associated with correcting potential material or tooling problems. The presented study verified the efficacy of a multivariate approach to set-point profiling.

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