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Automatic Tuning and Regulation of Injection Molding by the Virtual Search Method

Methodical specification of process inputs for injection molding is hindered by the absence of accurate analytical models. For these processes, the input variables are assigned either by trial and error, based on heuristic knowledge of an experienced operator, or by statistical Design of Experiments (DOE) methods which construct a comprehensive empirical model between the inputs and part quality attributes. In this paper, an iterative method of input selection (tuning) referred to as the Virtual Search Method (VSM) is introduced that conducts most of the search for appropriate machine inputs in a 'virtual' environment provided by an approximate input-output (I-O) model. VSM applies the inputs to the process only when it has exhausted the search based on the current I-O model. It evaluates the quality of inputs from the search and updates the I-O model for the next round of search based on measurements of part quality attributes (e.g., size tolerances and surface integrity) after each process iteration. According to this strategy, VSM updates the model only when needed, and thus selectively develops the model as required for tuning the process. This approach has been shown to lead to shorter tuning sessions than required by DOE methods.

1 Introduction

The demand for production of complex parts, required for improved functionality and ease of assembly, has necessitated injection molded parts with tighter tolerances and superior finish. This, in turn, has increased demands for more accurate control of the process (Agrawal et al., 1987; Amellal et al., 1994). Towards this objective, significant progress has been made in improving the stability of the process on-line (Chiu et al., 1991; Grolman and Nunn, 1991; Gao et al., 1994; Kazmer and Barkan, 1997). However, relatively little attention has been paid to efficient specification of setpoints for various machine inputs such as melt and mold temperatures, injection pressure, and injection speed. Ideally, these setpoints should be specified so as to produce parts with acceptable part quality attributes, which for an injection molded part would typically be size, surface topography, and/or mechanical properties (e.g., tensile strength, flexural strength).

The primary difficulty in selecting appropriate setpoints in injection molding is the complexity of the process and its variability. Polymers have extremely complex material properties: non-Newtonian, non-isothermal rheology together with highly temperature and pressure dependent thermal properties. During processing, the material undergoes temperature and pressure increases and significant shear deformation, followed by rapid decay of temperature and pressure in the cavity, leading to solidification and locking of residual stress, orientation, and other part properties that determine the molded part quality (Rohn, 1995). In addition to process complexity, process variability poses an impediment to maintaining the desired part quality during production. A major source of product inconsistency is variation in material properties (Vaatainen et al., 1994). For instance, small changes in viscosity, density, or composition may occur when one material is substituted by another having similar flow properties, regrind is mixed with virgin material, a material is used after it has been stored over an extended period of time, or a switch is made between different batches of the same material grade (Polinski et al., 1994). A second source of variability involves the process machinery. For instance, molding machines of different injection cylinder and clamp design will have very different machine dynamics, providing different levels of molded part quality for the same process set-points—even 'identical' molding machines from the same manufacturer can induce significant quality variation due to differences in machine controllers as well as varying amounts of wear in the melt and hydraulic delivery systems. Other sources of variability stem from human interaction (Morris and Rouse, 1985) and the physical environment in which the molding machine is operating (e.g., outdoor temperature may limit the effectiveness of evaporative coolers which may change the temperature of the plant water; humidity can affect the dryness of the materials entering the barrel which may introduce severe quality inconsistencies).

The traditional approach to machine input selection (tuning) in the plastics industry has been 'trial and error'. For this, shots are taken during start-up and part quality attributes are measured after each shot to evaluate the quality of produced parts. A human expert then uses his/her knowledge of the process to select the machine inputs in such a way as to improve the quality of the part from shot to shot. This tuning exercise is repeated until the specifications for part quality are satisfied. The main drawback of the traditional tuning approach is its inefficiency due to its 'ad hoc' nature. Humans usually use linear relationships to relate machine inputs to quality attributes, so they often have difficulty adjusting the inputs over large ranges (Moray et al., 1986). They also tend to treat the various attributes as independent, thus, ignore the couplings among the attributes. This and the added difficulty of coping with noise often lead to time-consuming tuning sessions and considerable waste.

An alternative to the traditional trial and error approach has been the use of 'expert systems'. Trouble-shooting expert systems, which have attracted considerable attention in recent years, represent corrective guidelines in the form of 'if-then' rules (Rogers, 1991; Kameoka et al., 1993; Farrel and Dzeskie-

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wicz, 1994), so they have the appeal of replacing the human expert in providing trouble-shooting knowledge. Expert systems, however, are limited by their non-quantitative nature and their inability to cope with quality issues not addressed by the rules.

A more methodical approach to tuning injection molding processes is Design of Experiments (DOE) (Schmidt and Launsby, 1988), where an empirical model is formed based on data obtained from a set of designed experiments. Based on this model, the objective function of an unconstrained optimization problem is defined as a function of the part quality attributes, and the set of inputs that produce the best quality attributes are obtained as the 'optimal' point of this optimization problem. While DOE-based methods offer a systematic approach to tuning that can also be used for mold qualification (Phadke, 1989; Budill, 1993; Martin et al., 1995; Michaeli and Vaculik, 1995; Michaeli et al., 1995; Vaatainen et al., 1995), they are only practical for large scale injection molding applications where the high cost associated with constructing a comprehensive empirical model can be justified.

The objective of this paper is to introduce a method of tuning for injection molding processes that incorporates aspects of both the trial and error approach and DOE. This method, analogous to the trial and error approach, uses measurements of part quality attributes to evaluate the inputs. It differs from this approach, however, in that like DOE methods it uses an input-output (I-O) model to select the inputs. In the proposed method, the inputs are applied to the process only when the search for them has been exhausted based on the current I-O model. As such, this method uses the I-O model as a "virtual" process and does not require feedback from the process for each iteration of the search. The method refers to the process to (1) test the feasibility of the inputs obtained from the current I-O model and (2) to update the I-O model using the measurements of part quality attributes obtained from the process. According to this scheme, the I-O model is updated only when it no longer provides guidance towards the feasible region. This method is hereafter referred to as the "Virtual Search Method (VSM)" to emphasize its interleaved approach to tuning and model development.

The VSM, which uses a discrete feedback control strategy, can also be referred to as an "adaptive zero-horizon stochastic-model predictive controller" (Camacho and Bordon, 1995). As in model predictive control (MPC), VSM uses an input-output (I-O) model to conduct the search and a search algorithm to select the process inputs. However, it is a drastically simplified MPC in that it only uses a static model and predicts the outputs for only the next step (zero-horizon). The reference to MPC is avoided here to prevent any misconceptions about its complexity.

2 Virtual Search Method

The task of tuning is synonymous with moving the process towards a feasible operating region defined by specifications of part quality. The proposed Virtual Search Method (VSM) uses measured attributes of part quality $\mathbf{g}(t)$ at the end of each cycle t to determine whether the produced part meets its quality specifications. It then determines appropriate modifications to the machine inputs for the next cycle, if any of the specifications are not met. The block diagram of this method is shown in Fig. 1. It consists of a "search algorithm" that determines prospective changes to the machine inputs for the next part, an "input-output (I-O) model" which estimates the corresponding changes to the part attributes, and a 'learning algorithm' to update the I-O model after each cycle based on part quality measurements. The analogy behind the design of this method is discussed below.

The customary procedure for tuning in the "trial and error" approach is to adjust the machine inputs, and use the relative improvement/deterioration of the part attributes as the basis for

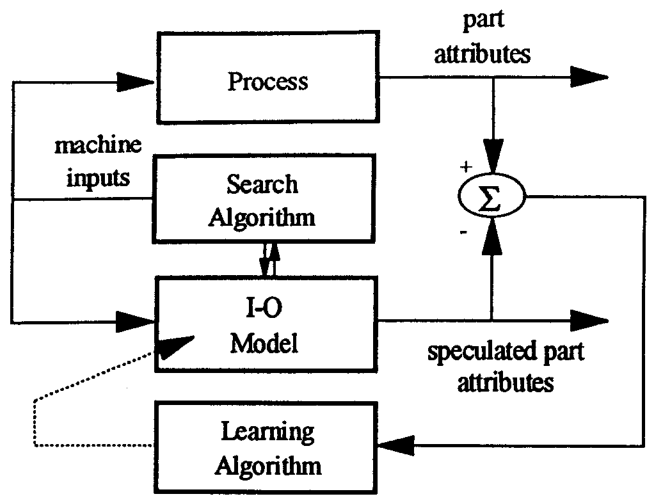

Fig. 1 Block diagram of the Virtual Search Method

further adjustment of these inputs. However, relying on direct process feedback can be costly, as many scraps may be produced before the process is tuned. In order to reduce this cost, the I-O model is incorporated in VSM to speculate the part attributes resulting from prospective changes, so that search can be performed based on the speculated values instead of measured attributes. Once the search algorithm produces a set of inputs with acceptable speculated attributes, actual measurements of part attributes can be obtained from the process. If the measured attributes are within their specifications training will be stopped until any subsequent part attributes fall outside the specifications. On the other hand, if the measured attributes are not within the specifications, the I-O model is updated so that the effects of prospective machine inputs on the part attributes can be more accurately speculated during the next round of operation of the search algorithm.

A key factor in the operation of VSM is the form of the I-O model, since it influences the structure of the search and learning algorithms. Like any other manufactured part, part attributes are only nominally uniform, and will vary according to some distribution. To represent the stochastic aspect of part quality attributes, the individual outputs of the I-O model $\hat{g}_j$, representing the speculated values of the part quality attributes, can be defined as normally distributed random variables $n_j \in \mathcal{N}(\bar{n}_j, \sigma_j)$. The simplest form of the I-O model, which defines the mean μ_j and standard deviation σ_j of the individual outputs, has the form

$$\mu_j = w_{0j} + w_{1j}x_1 + \ldots + w_{nj}x_n \tag{1}$$

$$\sigma_j = m_{0j} + m_{1j}x_1 + \ldots + m_{nj}x_n \tag{2}$$

where the coefficients $w_{.j}$ and $m_{.j}$ represent the influence of individual machine inputs on the mean and standard deviation of individual outputs. Both $w_{.j}$ and $m_{.j}$ are updated by the learning algorithm (Fig. 1) based on a sample set of part quality attribute measurements obtained for the current set of machine inputs. Although the learning algorithm updates the I-O model coefficients so as to cope with mild nonlinearities, the form of the I-O model itself may not be an adequate medium for representing severe nonlinearities. In cases where process nonlinearities are of major concern, a more sophisticated medium such as multi-layer neural networks can be used (Hunt et al., 1995; Maa and Shanblatt, 1992; Woll et al., 1996). The main advantage of these networks is that they can represent more accurately the nonlinearities of the process, so they may be able to tune the process in fewer iterations. Another advantage of these networks is their pattern-classification capability which would facilitate coping with noise in the measurements of part quality. Their disadvantage, however, is their demand for more extensive input-output data for training the network which could adversely affect tuning efficiency.

The form of the I-O Model is the basis for formulating the Search Algorithm (Fig. 1), which is to obtain machine inputs that produce parts with attributes' distributions within the specifications. This is synonymous with finding x such that

$$\max (\hat{\mathbf{g}}(\mathbf{x})) \leq \mathbf{g}_{\max} \tag{3}$$

$$\min (\hat{\mathbf{g}}(\mathbf{x})) \geq \mathbf{g}_{\min} \tag{4}$$

where $\mathbf{g}_{\max}$ and $\mathbf{g}_{\min}$ denote the upper and lower specifications on the part attributes, respectively. For the I-O model in the form of Eqs. (1) and (2), where μ_j and σ_j are both defined linearly in terms of the machine inputs, selecting machine inputs whose speculated part attributes satisfy the specifications is equivalent to finding a feasible solution to a Linear Programming (LP) problem. For this case, the Simplex Algorithm (Arora, 1989) can be used to perform the search, defining $\max(\hat{g}_j)$ and $\min(\hat{g}_j)$ as

$$\max (\hat{g}_j) = \mu_j + k\sigma_j \tag{5}$$

$$\min (\hat{g}_j) = \mu_j - k\sigma_j \tag{6}$$

where k represents a constant factor that would typically be set between 3 and 6. In cases where more complex I-O models are used, nonlinear programming algorithms such as sequential quadratic programming or generalized reduced gradient (Arora, 1989) can be utilized to perform the search.

As with the search algorithm, the learning algorithm needs to be selected based on the form of the I-O model. For example, for the linear model defined in Eqs. (1) and (2), the coefficients $w_{.j}$ and $m_{.j}$ can be updated iteratively using a weighted recursive least squares algorithm (Ljung, 1987). As such, the coefficients of the I-O Model can be considered as weighted averages of the observed gradients of the means and standard deviations of the attributes with respect to the machine inputs. In the case of a neural network as the I-O model, the network weights can be updated by error back propagation (Hinton et al., 1988).

An important issue in the applicability of VSM is its stability. Many results have been obtained for stability of model predictive control (MPC) (Clark, 1994), but even those that address constrained finite horizon control are derived for cases where a quadratic cost function is minimized and a dynamic model represents the process (Rawlings and Muske, 1993). Although the analytical results obtained from model predictive control literature are not directly applicable to VSM, they provide guidelines which can be used to evaluate the stability of VSM during application. The central conclusion of the stability results from MPC is that asymptotic stability is guaranteed if (1) there exists a feasible solution to the optimization problem, and (2) the cost function is monotonically decreasing (Camacho and Bordons, 1995). According to these results, it can be stated that VSM is stable if: (1) there consistently exist feasible regions for the updated I-O models, and (2) the part quality attributes continually converge toward their specifications. The second condition is basically satisfied if the feasible region of the I-O model continues to converge towards the feasible region of the process, as defined by the specifications of part quality attributes. By the same analogy, the lack of convergence of part attributes can be interpreted as the shortcoming of the I-O model's structure in representing the process. The convergence of the part quality attributes can be measured after each process iteration by an objective function in terms of the distance between the mean of the measured part attributes and their respective target values, as

$$D(t) = \sum_{j=1}^{N} |\tau_j - \bar{g}_j(t)| \tag{7}$$

where $\bar{g}_j(t)$ denotes the average value of the jth part quality attribute measured from the parts produced after the tth process iteration, and τ_j represents the jth target attribute defined as

$$\tau_j = \frac{g_{j\max} + g_{j\min}}{2} \tag{8}$$

to denote the jth coordinate of the feasible region for a two sided specification. Note that although the objective function $D(t)$ has no influence on the computation of the machine inputs, its value after each process iteration provides feedback about the overall performance of VSM and the suitability of its I-O model.

3 An Investigation

The performance of VSM was first evaluated in simulation using DOE models obtained for various injection molding applications (Budill, 1993)—these models represent the "Process" block in Fig. 1. The DOE models, which were used to simulate the part quality attributes for each set of machine inputs, define the means and standard deviations of the normal distributions associated with individual attributes by quadratic relationships of the form:

$$\mu_j = w_{0j} + \sum_{j=1}^{n} w_j x_j + \sum_{i,j=1}^{n} k_{ij} x_i x_j$$

$$\sigma_j = m_{0j} + \sum_{j=1}^{n} m_j x_j + \sum_{i,j=1}^{n} l_{ij} x_i x_j$$

The details of these relationships are in (Budill, 1993) and excluded here for brevity.

In this simulation study, a simple linear model in the form of Eqs. (1) and (2) was used as the I-O model. An objective here was to evaluate the applicability of a simple I-O model in a case with mild nonlinearities (quadratic form). The search algorithm used for this study was the Simplex algorithm. The Simplex algorithm is composed of two phases. The first phase is designed to locate the feasible region and the second phase to minimize an objective function within the feasible region. For this problem, the first phase of the Simplex algorithm was used to search for the machine inputs that produce parts with acceptable speculated attributes. The Simplex algorithm uses an iterative approach where the attribute that is the least acceptable is addressed first. For the attribute in question, the algorithm changes the input with the greatest ability to move the attribute towards its specification. It then updates the other speculated attributes accordingly. This procedure is repeated with the updated speculated attributes until all of the speculated attributes are within the specifications or no further improvement is possible.

As with the search algorithm, the learning algorithm was selected according to the form of the I-O model. For the linear stochastic model defined in Eqs. (1) and (2), the coefficients $w_{.j}$ and $m_{.j}$ were updated iteratively using a weighted recursive least squares (RLS) algorithm (Ljung, 1987). Using RLS, the parameter vectors $\mathbf{W}_j = \{w_{.j}\}$ (and $\mathbf{M}_j = \{m_{.j}\}$) were updated as

$$\mathbf{W}_j(k) = \mathbf{W}_j(k-1) + \frac{\mathbf{P}(k-1)\mathbf{x}(k)}{\lambda + \mathbf{x}(k)^T\mathbf{P}(k-1)\mathbf{x}(k)} [\mu_j(k) - \hat{\mu}_j(k)] \tag{9}$$

$$\mathbf{P}(k) = \frac{1}{\lambda}\left[\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{x}(k)\mathbf{x}(k)^T\mathbf{P}(k-1)}{\lambda + \mathbf{x}(k)^T\mathbf{P}(k-1)\mathbf{x}(k)}\right] \tag{10}$$

where $\mathbf{x}(k)$ is the vector of process inputs, $\mu_j(k)$ denotes the mean of the jth attribute from the sample set of measurements obtained for the current input vector (simulated in this case)

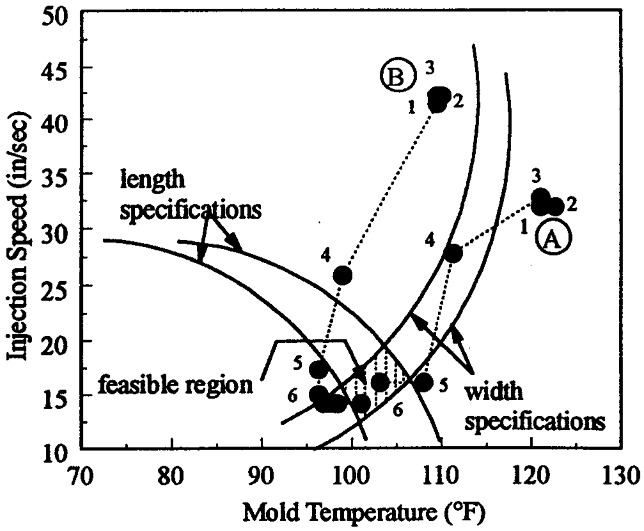

Fig. 2 Machine input values obtained from two runs of VSM with different initial conditions

and $\hat{\mu}_j(k-1)$ represents the mean estimate of the attribute from the I-O model, k denotes the process iteration, $\mathbf{P}(k)$ is the matrix of estimation gains, and λ is the "forgetting factor" (Ljung, 1987) used to give more weight to the new data for mild nonlinearities. Estimates of parameter vector $\mathbf{M}_j = \{m_{.j}\}$ were obtained similarly by replacing μ with σ in the above formula.

Two simulation cases are presented here. The first case consists of two machine inputs: mold temperature x_1 (°F) and injection speed x_2 (in./sec), and two dimensional attributes: part length g_1 (in.) and part width g_2 (in.). The second case has two additional inputs: melt temperature x_3 (°F) and injection pressure x_4 (psi), and an additional output: flash ordinal g_3, which was represented by an additional quadratic relationship in the simulation model. The first case with only two inputs allows graphical depiction of VSM's performance in two dimensional space, and the second case with a larger number of inputs and outputs provides a more realistic basis for evaluating VSM's efficiency.

In both cases, for each new set of machine inputs ten sets of part attributes were generated randomly within their respective distributions to represent the stochastic aspect of the process. In the cases presented here, the first set of inputs was selected randomly and the next n sets (n = number of inputs) were obtained by perturbing each input one at a time. These inputs and the corresponding simulated outputs were then used to update the I-O model (initially set to identity).

The results obtained from two separate runs of VSM for the first case are presented in Fig. 2. In this figure, the upper and lower limits on the part attributes:

$$1.6102 \text{ in.} \leq g_1 = g_1(n_1, \sigma_1) \leq 1.6142 \text{ in.} \tag{11}$$

$$1.5157 \text{ in.} \leq g_2 = g_2(n_2, \sigma_2) \leq 1.5197 \text{ in.} \tag{12}$$

are shown in the input space to indicate the coordinates of the machine inputs with respect to the feasible region as defined by the bounds on the part attributes. The results presented from these two runs (A and B) in Fig. 2 demonstrate that the performance of VSM depends on the initial machine inputs and that the feasible region was reached in six iterations in run A and ten iterations in run B. On the average, VSM reached the feasible region in approximately eight iterations (ranging between 3 and 14) for 20 runs. Given that the effectiveness of VSM depends on whether the I-O model can ultimately represent the feasible region of the process, VSM's speed of convergence would depend upon how fast the I-O model can be adapted to provide such a representation. The results obtained from this study indicate that the linear first order I-O model considered here was capable of representing the feasible region of a process defined by quadratic relationships.

Table 1 Comparison of the number of process iterations between VSM and DOE

Method	Inputs	Outputs	No. of Iterations Mean	Max	Min	Runs
VSM	2	2	7.5	14	3	20
DOE	2	2	9	-	-	-
VSM	4	3	11.3	18	6	20
DOE	4	3	27	-	-	-

Another issue in the applicability of VSM is its efficiency and speed of convergence, particularly in comparison to DOE. In contrast to the interleaved approach to modeling and search by VSM, the DOE method constructs a comprehensive empirical model of the relationships between machine inputs and part quality attributes and optimizes this model to obtain suitable machine inputs. As such, the number of process iterations needed by DOE to construct the model is determined by the number of machine inputs. In order to compare this aspect of VSM's operation, the numbers of experiments (process iterations) needed by each method for the two simulation cases are shown in Table 1. In comparison to DOE, the maximum number of process iterations for the first case (two inputs and two outputs) is larger for VSM, but the average number of process iterations is smaller. In the second case (four inputs and three outputs), however, VSM's maximum number of process iterations is significantly less than DOE's. These results indicate that VSM is less sensitive to the number of inputs than DOE, therefore it is more efficient when several inputs need to be selected for tuning the process.

4 Experimental

The effectiveness of VSM was investigated experimentally using a Toyo PLASTAR model Ti-90G2 injection molding machine with 90 US ton clamping force and 9.9 cu. in. capacity. The mold was a single-part mold which was filled with a 90/10 virgin/regrind mix of polypropylene to make ASTM plaques (approx. 2 in. by 4 in. by 0.125 in.). The machine inputs that were adjusted for tuning the process were: the mold temperature (°F), melt temperature (°F), injection pressure (psi), and injection speed (in./sec), and the part attributes measured for each

Table 2 Values of machine inputs selected by VSM for each process iteration

Process Iteration	Mold Temp. (°F)	Melt Temp. (°F)	Inj. Pressure (psi)	Inj. Speed (in./sec)
1	80	380	565	41
2	105	415	650	35
3	110	425	650	35
4	110	425	575	35
5	120	425	575	35
6	120	420	575	35
7	120	410	525	35
8	120	420	525	35
9	130	420	525	35
10	110	410	525	35
11	110	410	525	35
12	110	410	525	35

Table 3 Values of part attributes obtained from the ten parts produced for each process iteration. Parameter D represents the sum of the absolute distances of the part attributes from their target values.

Process Iteration	Max Length (in)	Min Length (in)	Max Width (in)	Min Width (in)	$D(t)$
1	3.9737	3.9729	1.9530	1.9517	0.0083
2	3.9723	3.971	1.9526	1.9503	0.0059
3	3.9697	3.9693	1.9488	1.9471	0.0013
4	3.9702	3.9692	1.9483	1.9471	0.0018
5	3.9704	3.9685	1.9468	1.9441	0.0038
6	3.9709	3.9689	1.9486	1.9447	0.0030
7	3.9692	3.9680	1.9466	1.9435	0.0037
8	3.9703	3.9689	1.9457	1.9436	0.0047
9	3.9692	3.9683	1.9458	1.9416	0.0048
10	3.9695	3.9688	1.9490	1.9466	0.0011
11	3.9694	3.9685	1.9505	1.9467	0.0003
12	3.9694	3.9681	1.9485	1.9471	0.0007

part were the width and length of the plaque. The measurements were taken by two Ono Sokki EG-225 size gages mounted in a frame together with a brace and a clamp for positioning and securing the part, so as to provide consistent measurements of the part's width and length with an accuracy of ±0.00005 in. on fully cooled parts. Since the effect of shrinkage was of particular concern in these parts, they were allowed to cool before size measurements were taken. The upper and lower bounds for the machine inputs were set as $\mathbf{X}_{ub}$ = [130°F, 430°F, 650 psi, 45 in./sec] and $\mathbf{X}_{lb}$ = [80°F, 380°F, 400 psi, 15 in./sec] and the upper and lower specifications for width and length were selected as $\mathbf{g}_{max}$ = [3.9695 in., 1.9510 in.] and $\mathbf{g}_{min}$ = [3.9680 in., 1.9460 in.], respectively.

As with the example of Section 3, a linear stochastic model was used as the I-O model and the Simplex algorithm as the search algorithm. After each change in the inputs, the machine was run for 15–30 minutes so that the change could take effect. Ten parts were measured for each set of inputs so as to provide the statistical basis for forming the I-O model. Tuning began with the first two sets of machine inputs randomly selected within their respective upper and lower limits as $\mathbf{x}(1)$ = [80°F, 380°F, 565 psi, 41 in./sec] and $\mathbf{x}(2)$ = [105°F, 415°F, 650 psi, 35 in./sec]. These inputs resulted in parts with maximum and minimum measurement values of width and length as $\mathbf{g}_{max}(1)$ = [3.97365 in., 1.95295 in.], $\mathbf{g}_{min}(1)$ = [3.9729 in., 1.9517 in.], $\mathbf{g}_{max}(2)$ = [3.9723 in., 1.9526 in.], and $\mathbf{g}_{min}(2)$ = [3.9710 in., 1.9503 in.]. The measurements from the first iteration did not meet their specifications—the minimum length and width measurements were both larger than their respective upper and lower specifications. For the second process iteration the minimum length and maximum width measurements were greater than their upper specifications. Although these measurements were not within their specifications, the variance of the length and width measurements were less than the variances of their respective specifications. As such, it was only necessary to change the mean values of the measurements, and not their variances.

After these two process iterations, the I-O model (initially set as an identity matrix) was updated so as to better guide the search for new machine inputs. The machine inputs selected by VSM and the measurements obtained from the produced parts are listed in Tables 2 and 3, respectively, and plotted in Figs. 3, and 4. The results indicate that the modifications to the machine inputs continually improved part quality by bringing the length and width measurements closer to their specifications. Note that over the first six iterations, although the changes to the machine inputs improved the overall part measurements, the I-O model was never so accurate as to result in acceptable parts until the tenth process iteration. The process was continued for two more iterations of ten parts each with these inputs so as to confirm their acceptability. Included in Table 3 are the values of parameter D (Eq. 7), which indicate the progress of the part quality attributes toward their target values.

5 Discussion

The results obtained from both the simulation and experimental evaluation of VSM indicate that it is a viable method for tuning injection molding machines. Several issues related to the performance of this method and its implementation are discussed next.

- Comparison to DOE Methods: As discussed in Section 1, the fundamental difference between VSM and the DOE methods is in model development. DOE methods develop a comprehensive model of the process *a priori* and then use it as the basis for selecting the optimal machine inputs. In contrast, VSM interleaves model development and search for the inputs by developing the model as needed. The premise here is that VSM can reach the feasible region of the process without constructing a comprehensive model, and thus may require less experimentation. While the faster convergence of VSM may be of considerable value to small job operations, the fact that the inputs are not optimal may be a drawback in larger operations, where the savings obtained from optimal settings may justify the cost of experimentation for a more comprehensive model. Of course, the mechanism to search for the optimal settings can be incorporated in VSM, but that will undoubtedly prolong the search process. The comparison between such a modified VSM and DOE is the subject of future research.

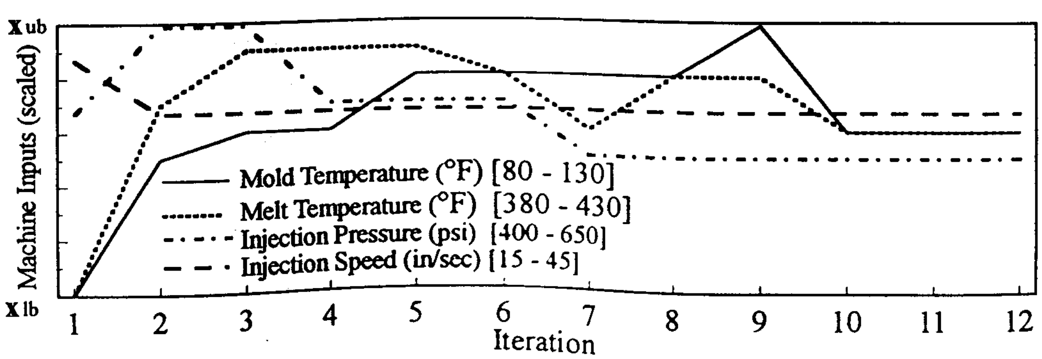

Fig. 3 Normalized machine input values selected by VSM

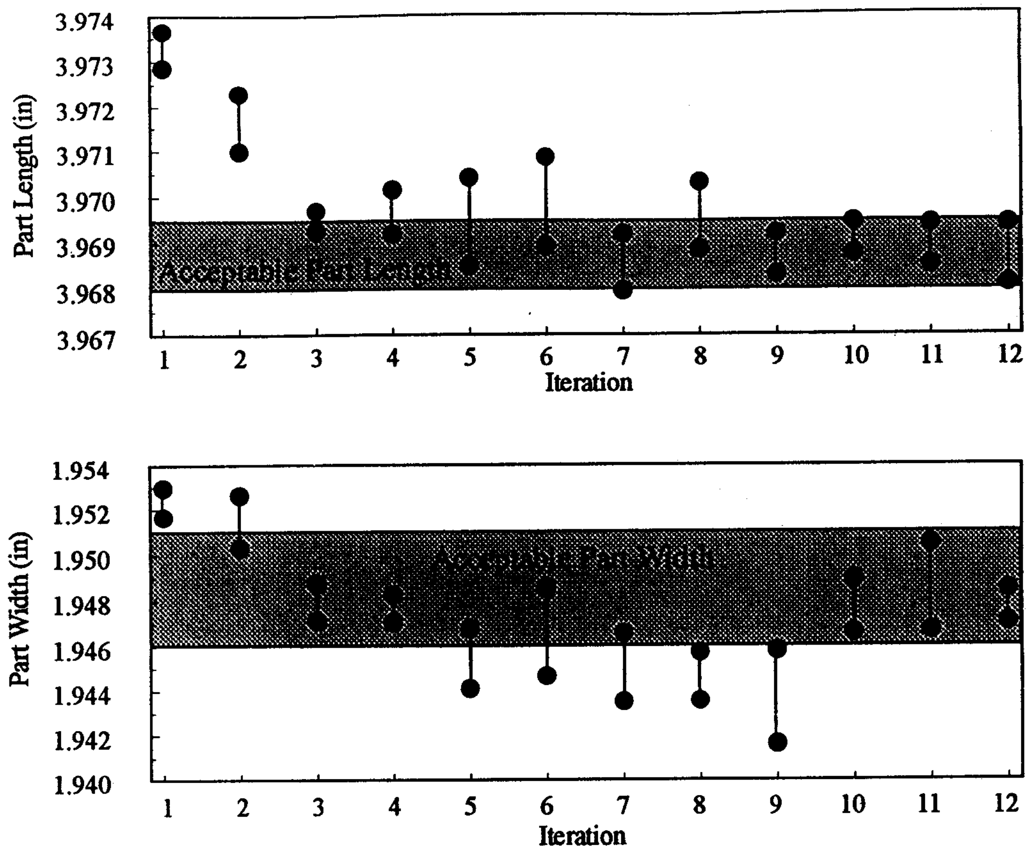

Fig. 4 Range of lengths and widths of the ten parts produced at each process iteration

- Robustness. The stability of VSM was discussed in Section 2. The main issue in VSM's robustness is the effectiveness of the I-O model in defining the feasible region of the process. While it is shown in this paper that a linear stochastic I-O model can perform this function for moderately nonlinear processes (see the results in Section 3), there is always the possibility that the I-O model may not be suitable in form. To provide feedback to the operator about the suitability of the I-O model, an objective function which quantifies the distance of the part attributes from their target values [e.g., Eq. (7)] can be used. In cases where successive values of D indicate no progress, a more complex form of the I-O model can be considered. From an application point of view, the software which implements VSM can be provided with various I-O model forms along with corresponding search and learning algorithms, so that models with higher levels of complexity can be selected to improve convergence.
- Further Development. VSM is designed to operate with any number of machine inputs and quality attributes through a modular architecture permitting different structures of I-O models, search algorithms and learning algorithms. Although preliminary results have indicated that VSM is a viable method for input selection in a controlled environment, it can be extended further to enhance its applicability as a generic method of process regulation in production. One such extension is incorporation of process dynamics in the I-O model so as to eliminate the delay required for allowing the process to reach steady state. Another extension could be allowing characterization and incorporation of aspects of part quality that are difficult to quantify, such as surface quality and burn marks. A possible scenario for consideration of qualitative attributes in the input selection process is to specify them as fuzzy variables with pre-specified membership functions (Zadeh, 1965; Bandemer and Nather, 1992). Using this strategy, the components of the I-O model associated with these qualitative attributes would represent the means and standard deviations of their membership functions which, in turn, can be considered as sub-components of the I-O model that need to be updated based on new measures of qualitative attributes.

6 Conclusions

Current input selection methods for injection molding are often inadequate for stringent applications. A few approaches have been proposed to address this issue, including expert system troubleshooting software, and structured experimental design methods. These approaches are inadequate in that they, respectively, cannot consider quality issues beyond their knowledge base, and require excessive investment in operator training and molding trials. This paper introduces an input selection method that interleavs the tasks of search and model development. Therefore, it uses the model like a "virtual" process and refers to the process only after it has exhausted the search based on this model. The results presented in this paper indicate that the proposed method is viable. Some issues related to its implementation have also been discussed.

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References

Agrawal, A. R., Pandelidis, I. O., and Pecht, M., 1987, "Injection-Molding Process Control—A Review," *Polymer Engineering and Science*, Vol. 27, pp. 1345–1357.

Amellal, K., Tzoganakis, C., Penlidis, A., and Rempel, G. L., 1994, "Injection Molding of Medical Plastics: A Review," *Advances in Polymer Technology*, Vol. 13, No. 4, pp. 315–322.

Arora, J. S., 1989, *Introduction to Optimum Design*, McGraw-Hill, Inc., New York, New York.

Bandemer, H., and Nather, W., 1992, *Fuzzy Data Analysis*, Kluwer Academic Publishers.

Budill, K., 1993, *A Systematic Approach to Tool Qualification for Injection Molding*, Master's thesis, Massachusetts Institute of Technology, Boston, MA.

Camacho, E. F., and Bordons, C., 1995, *Model Predictive Control in the Process Industry*, Springer, London.

Chiu, C. P., Wei, J. H., and Shih, M. C., 1991, "Adaptive Model Following Control of the Mold Filling Process in an Injection Molding Machine," *Polymer Engineering and Science*, Vol. 31, p. 15.

Clark, D., ed., 1994, *Advances in Model-Based Predictive Control*, Oxford University Press, Oxford.

Farrell, R. E., and Dzeskiewicz, L., 1994, "Expert System for Injection Molding," *SPE ANTEC Conference Proceedings*, San Francisco, CA, pp. 692–695.

Gao, F., Patterson, W. I., and Kamal, M. R., 1994, "Self-tuning Cavity Pressure Control of Injection Mold Filling," *Advances in Polymer Technology*, Vol. 13, p. 111.

Grolman, C. P., and Nunn, R. E., 1991, "Adaptive Process Control for Injection Molding," *J. of Reinforced Plastics and Composites*, Vol. 9, p. 2121.

Hinton, D. E., Rumelhart, G. E., and Williams, R. J., 1988, "Learning Error Representation by Error Propagation," *Parallel Distributed Processing—Explorations in the Microstructure of Cognition*, D. E. Rumelhart and J. L. McClelland, eds., The MIT Press, Cambridge, MA, 1988.

Hunt, K., Irwin, G., and Warwick, K., 1995 *Neural Network Engineering in Dynamic Control Systems*, Springer, New York.

Kameoka, S., Haramato, N., and Sakai, T., 1993, "Development of an Expert System for Injection Molding Operations," *Advances in Polymer Technology*, Vol. 12, No. 4, pp. 403–418.

Kazmer, D. O., and Barkan, P., 1997, "Multi-cavity Pressure Control During the Filling and Packing Stages of Injection Molding," *Polymer Engineering and Science*, Vol. 37, No. 11, pp. 1865–1895.

Ljung, L., 1987, *System Identification: Theory for the User*, Prentice-Hall, Inc., Englewood Cliffs, New Jersey.

Maa, C. Y., and Shanblatt, M. A., 1992, "A Two-Phase Optimization Neural Network," *IEEE Trans. on Neural Networks*, Vol. 3, No. 6, p. 1003.

Martin, M. F., Bontumasi, F., and Young, G., 1995, "The Practical Application of Design of Experiments in the Total Quality Injection Molding Process," *SPE ANTEC Conference Proceedings*, Boston, MA, pp. 4041–4045.

Michaeli, W., and Vaculik, R., 1995, "Closed Loop Quality Control for Injection Molding based on Statistical Process Models," *SPE ANTEC Conference Proceedings*, Boston, MA, pp. 4046–4050.

Michaeli, W., Vaculik, R., and Bluhm, R., 1995, "Reprocessing of Recyclat-On-Line Prediction of Quality Attributes," *SPE ANTEC Conference Proceedings*, Boston, MA, pp. 4051–4057.

Moray, N., Lootsteen, P., and Pajak, J., 1986, "Acquisition of Process Control Skills," *IEEE Trans. Syst., Man, and Cybernetics*, Vol. SMC-16, p. 697.

Morris, N. M., and Rouse, W. B., 1985, "The Effects of Type of Knowledge Upon Human Problem Solving in a Process Control Task," *IEEE Trans. Syst., Man, and Cybernetics*, Vol. SMC-15, p. 698.

Phadke, M., 1989, *Quality Engineering Using Robust Design*, Prentice Hall, Englewood Cliffs, New Jersey.

Polinski, A. J., Deborski, C. A., and Aslam, S., 1994, "Effects of Small Changes in the Melt Viscosity on the Filling and Packing Stages of Injection Molding," *Proc. of Annual Technical Meeting of the Society of Plastics Engineers*, Vol. 52, p. 659.

Rawlings, J. B., and Muske, K. R., 1993, "The Stability of Constrained Receding Horizon Control," *IEEE Trans. on Aut. Control*, Vol. 38, No. 10, pp. 1512–1516.

Rohn, C. L., 1995, *Analytical Polymer Rheology : Structure-Processing-Property Relationships*, Hanser Publications, Munich.

Rogers, J. K., 1991, " 'Intelligent' Molding: Expert Systems are Coming on Line Now," *Modern Plastics*, Vol. 68, pp. 56–60.

Schmidt, S., and Launsby, R., 1988, *Understanding Industrial Designed Experiments*, Air Academy Press, Colorado Springs, Colorado.

Vaatainen, O., Jarvela, P., Valta, K., and Jarvela, P., 1994, "The Effect of Processing Parameters on the Quality of Injection Moulded Parts by Using the Taguchi Parameter Design Method," *Plastics, Rubber and Composites Processing and Applications*, Vol. 21, No. 4, pp. 211–217.

Woll, S., Souder, P., and Cooper, D., 1996, "On-line Pattern Based Quality Monitoring for the Injection Molding Process," *Polymer Engineering and Science*, Vol. 36, No. 11.

Zadeh, L., 1965, *Fuzzy Sets, Information and Control*, Vol. 8, pp. 338–353.