Automatic Tuning of Injection Molding by the Virtual Search Method

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Methodical tuning of injection molding is not always possible because of the absence of accurate and reliable models for all the diverse quality characteristics encountered. An iterative method for automatic tuning of the molding process is the Virtual Search Method (VSM), which develops on-line a 'virtual' model of the process as the basis of search for the appropriate inputs. VSM resorts to the physical process only when it has exhausted the virtual search. Simulation and experimental investigations indicate that this approach leads to shorter tuning sessions than those required by Design of Experiments.

INTRODUCTION

The need for minimal assembly times, reduced tooling costs, and ease of recycling demands mechanical systems comprised of fewer, more complex components with increased functional requirements. This demand for production of complex parts has necessitated injection molded parts with tighter tolerances and superior finish. This, in turn, has increased demands for more accurate control of the process (1). While significant progress has been made in improving the stability of the process on-line (2–5), 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).

A typical commercial component is molded with the goal of minimizing material and processing costs subject to ten critical dimensional tolerances plus five additional surface and structural requirements. The molding process is typically over-constrained, with selection of the operating setpoints effecting the resulting part attributes in a non-deterministic manner. 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. This deformation is followed by rapid decay of temperature and pressure in the cavity, causing solidification and locking of residual stress, orientation, and other part properties that determine the molded part quality. In addition to process complexity, process variability poses an impediment to maintaining the desired part quality during production. Such process variability may stem from material, machine, operator or environment.

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 acceptability of produced parts. The process engineer 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 (6). Furthermore, they also tend to treat the various attributes as independent, thus, ignore the couplings among the attributes. These heuristic conceptual models and the added difficulty of coping with noise often lead to time-consuming tuning sessions and considerable waste. Often, process setpoints are selected that produce a significant percentage of defects while operating with extended processing times.

Commercial molders have realized the economic impact of limitations in their operational ability, and are

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purchasing auxiliary quality systems. One alternative offering to the traditional trial and error approach has been the use of 'expert systems.' Troubleshooting expert systems, which have attracted considerable attention in recent years, represent corrective guidelines in the form of 'if-then' rules (7–9), so they have the appeal of replacing the human expert in providing trouble-shooting knowledge. However, expert systems have not yet proven successful for injection molding since a generalized set of rules may not be appropriate across a broad range of part geometries, material properties, and machine dynamics. Expert systems are limited by their non-quantitative nature and their inability to cope with quality issues not addressed by the developed and inferenced rules.

A more methodical approach to tuning injection molding processes is Design of Experiments (DOE) where an empirical model is formed based on data obtained from a set of designed experiments (10). Based on this model, the objective function of an unconstrained optimization problem is defined in terms 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 methods offer a systematic approach to tuning that can be used for mold qualification (11), they are most practical for injection molding applications where the high cost associated with development of a comprehensive empirical model can be justified.

The objective of this paper is to discuss 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.

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 Virtual Search Method (VSM) uses measured attributes of part quality $g(t)$ at the end of each cycle t to determine whether the produced part meets its quality specifications (12). 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.

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 part attributes. Once the search algorithm produces a set of inputs with acceptable speculated attributes, the process is run with these inputs so the actual part attributes can be measured. 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 ran-

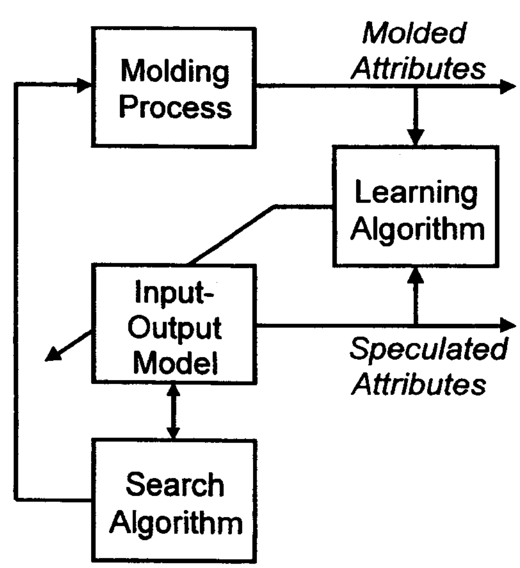

Fig. 1. Diagram of Virtual Search Method.

dom variables $n_j \in N(\mu_j, \sigma_j)$. 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

$$\mu_j = w_{0j} + w_{1j}x_1 + \cdots + w_{nj}x_n \quad (1)$$

$$\sigma_j = m_{0j} + m_{1j}x_1 + \cdots + m_{nj}x_n, \quad (2)$$

where the coefficients w_j and m_j represent the influence of individual machine inputs on the mean and standard deviation of individual outputs. These coefficients 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 present in the injection molding process. In cases where process nonlinearities are of major concern, a more sophisticated medium such as multi-layer neural networks can be used (14, 15).

The form of the I-O Model is the basis for formulating the Search Algorithm, which is to obtain machine inputs that produce parts with attribute(s) distributions within the specifications. This is synonymous with finding $\mathbf{x}$ such that

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

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

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 (16) can be used 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. 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.

SIMULATION RESULTS

The performance of VSM was first evaluated in simulation using DOE models obtained for various injection molding applications—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. (For details see (17)).

In this simulation study, a linear model in the form of *Eqs 1* and *2* was used as the I-O model. An objective 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. 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 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 (13). Using RLS, the parameter vectors $\mathbf{W}_j = \{w_j\}$ were updated

$$\mathbf{W}_j(k) = \mathbf{W}_j(k-1) + \frac{\mathbf{P}(k-1)\mathbf{x}(k)}{\lambda + \mathbf{x}(k)^T\mathbf{P}(k-1)\mathbf{x}(k)}[\mu_j(k) - \hat{\mu}_j(k)] \quad (5)$$

$$\mathbf{P}(k) = \frac{1}{\lambda}\left[\mathbf{P}(k-1) - \frac{\mathbf{P}(k-1)\mathbf{x}(k)\mathbf{x}(k)^T\mathbf{P}(k-1)}{\lambda + \mathbf{x}(k)^T\mathbf{P}(k-1)\mathbf{x}(k)}\right], \quad (6)$$

where $\mathbf{x}(k)$ represents 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) and $\hat{\mu}_j(k)$ 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' (13) used to give more weight to the new data for mild nonlinearities. Estimates of parameter vector $\mathbf{M}_j$ were obtained similarly by replacing μ with σ in the above formula.

Multiple simulation runs were performed to represent the effects of mold temperature, injection speed, melt temperature, and injection pressure on quality attributes such as part length, part width, and flash. 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 two sets were obtained by perturbing each input individually. These inputs and the corresponding 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,

$$40.48\ mm \leq g_1 = g_2(\mu_1, \sigma_1) \leq 40.58\ mm \quad (7)$$

$$38.10\ mm \leq g_1 = g_1(\mu_1,\sigma_1) \leq 38.20\ mm, \quad (8)$$

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 two runs (A and B) 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 average, VSM reached the feasible region in approximately eight iterations across 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. These results 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.

EXPERIMENTAL RESULTS

The effectiveness of VSM was also investigated experimentally using a Toyo PLASTAR model Ti-90G2 injection molding machine with 90 U.S. ton clamping force and 160 cc capacity. The mold was a single-part mold that was filled with a 90/10 virgin/regrind mix of polypropylene to make ASTM plaques (approx. 50 mm by 100 mm by 3 mm). The following machine inputs were adjusted: mold temperature, melt temperature, injection pressure, and injection speed. The width and length of the plaque were measured as part attributes by two Ono Sokki EG-225 size gauges with an accuracy of ±0.001 mm 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 $\mathbf{x}_{ub}$ = [54 C, 221 C, 4.5 MPa hydraulic, 1100 mm/sec] and $\mathbf{x}_{lb}$ = [27 C, 190 C, 2.8 MPa hydraulic, 380 mm/sec]. The upper and lower specifications for width and length were selected as $\mathbf{g}_{max}$ = [99.79 mm, 49.05 mm] and $\mathbf{g}_{min}$ = [99.76 mm, 48.92 mm], respectively.

As with the simulation results, 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 $\mathbf{x}(1)$ = [27 C, 193 C, 3.9 MPa hydraulic, 1030 mm/sec] and $\mathbf{x}(2)$ = [41 C, 213 C, 4.5 MPa hydraulic, 880 mm/sec]. This initial set of inputs resulted in

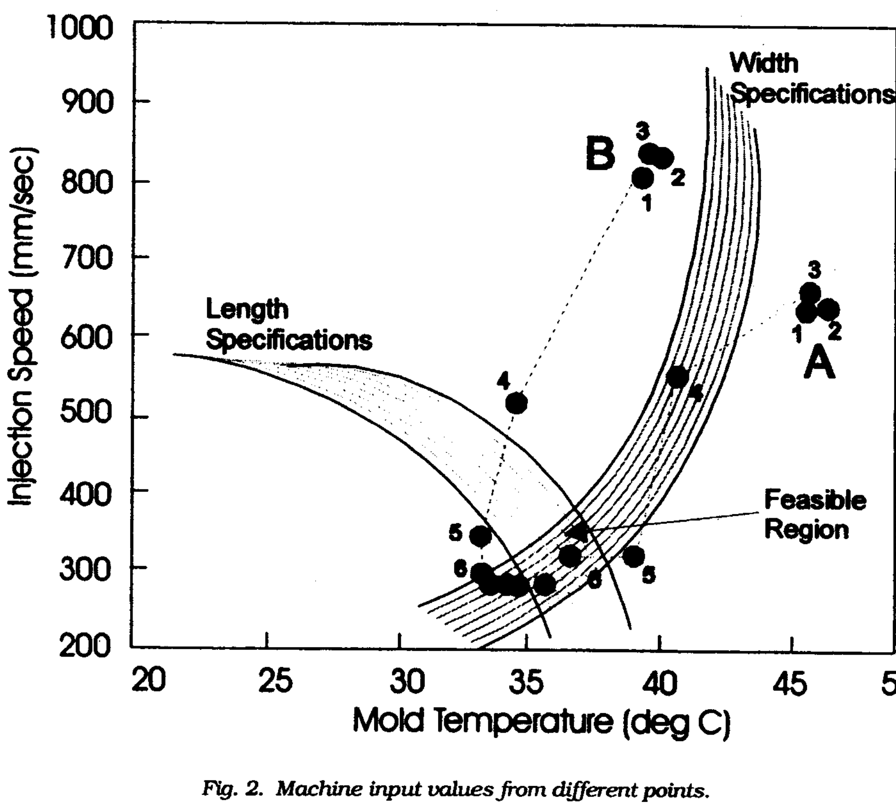

Fig. 2. Machine input values from different points.

parts that were not within specifications, though the variance of the length and width measurements were less than the specified range. As such, it was only necessary to change the mean values of the measurements and not the variances.

After two process iterations, the I-O model (initially set as an identity matrix) was updated to guide the search for new machine inputs. The machine inputs selected by VSM and the measurements obtained from the produced parts are listed in *Table 1*. 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.

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

The fundamental difference between VSM and 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 runs, the fact that the inputs are not optimal may be a drawback in longer runs, where the savings obtained from optimal settings may justify the cost of experimentation for a more comprehensive model. The mechanism to search for the optimal settings can be incorporated in VSM, but will extend the search process.

Robustness

The primary robustness issue in VSM's performance 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, 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 that quantifies the distance of the part attributes from their target values after each tuning iteration can be used. In tuning cases where no progress is made, a more complex form of the I-O model can be considered. From an application point of view, the software that 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.

FUTURE WORK

Based on interactions with the plastics industry, four improvement areas have been identified for VSM development. First, the VSM can be made more efficient and reliable by initializing the I-O model based on the qualitative knowledge of the process. For instance, a model coefficient can be initially set to represent an inverse relationship between part shrinkage and pack pressure. The authors are also investigating the use of advanced forms of the I-O model to better capture process non-linearities.

Second, the VSM can be modified towards optimizing conflicting objectives. Such conflicting objectives in industry might include multiple cavity molds, tight tolerance molding, and cycle time minimization. The VSM is currently a constraint-based quality controller in that the tuning process continues until all the molded part quality attributes are acceptable. How-

Table 1. Molding Tuning Process Guided by VSM.

k	Mold Temp. (C)	Melt Temp. (C)	Hyd. Pres. (MPa)	Inj. Speed (mm/s)	Mean Length (mm)	Mean Width (mm)
1	26.7	193.3	3.9	1041.4	100.922	49.590
2	40.6	212.8	4.5	889.0	100.880	49.567
3	43.3	218.3	4.5	889.0	100.825	49.478
4	43.3	218.3	4.0	889.0	100.830	49.472
5	48.9	218.3	4.0	889.0	100.824	49.414
6	48.9	215.6	4.0	889.0	100.824	49.445
7	48.9	210.0	3.6	889.0	100.802	49.404
8	48.9	215.6	3.6	889.0	100.828	49.394
9	54.4	215.6	3.6	889.0	100.806	49.370
10	43.3	210.0	3.6	889.0	100.816	49.474
11	43.3	210.0	3.6	889.0	100.811	49.494
12	43.3	210.0	3.6	889.0	100.806	49.474

ever, the molder may require that given acceptable quality the cycle time should be minimized as well. This functionality could be provided within the current implementation by defining a cost function based on cycle time and defect level. At the start of the tuning process, the cost specification could be set artificially high such that it would not affect the tuning of the process. Once acceptable parts are molded, the cost constraint can be dynamically tightened until the process is operating at a saturated point that is an optimal trade-off between quality and cost.

Third, the VSM may be extended to consider qualitative attributes and requirements as well. Since many molded part attributes are not continuously measurable (as with dimensions), the VSM would need to be able to qualitatively model the occurrence of discrete defects (e.g. burn marks or splay). Currently, the VSM can correct such defects when an operator provides numerical estimates of the qualitative attributes. For instance, the level of short shot specified between 0 and 10. The user-interface and VSM performance may be further improved through the use of fuzzy I-O models.

Finally, models for automatic quality assurance may be incorporated within the VSM. Automated quality assurance through VSM requires that VSM be directly interfaced to the machine controller or sensors. It is anticipated that machinery or controller suppliers to the plastics industry will provide such integration by implementing the VSM within their product offerings.

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 interleaves the tasks of search and model development, using the model as a 'virtual' process and referring to the process only after it has exhausted the search based on this model. The results presented in this paper indicate that the method is viable and, with further improvements, could greatly affect the plastics industry.

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