

# INJECTION MOLDING

MANUFACTURING

: Shoot | Shape | Ship

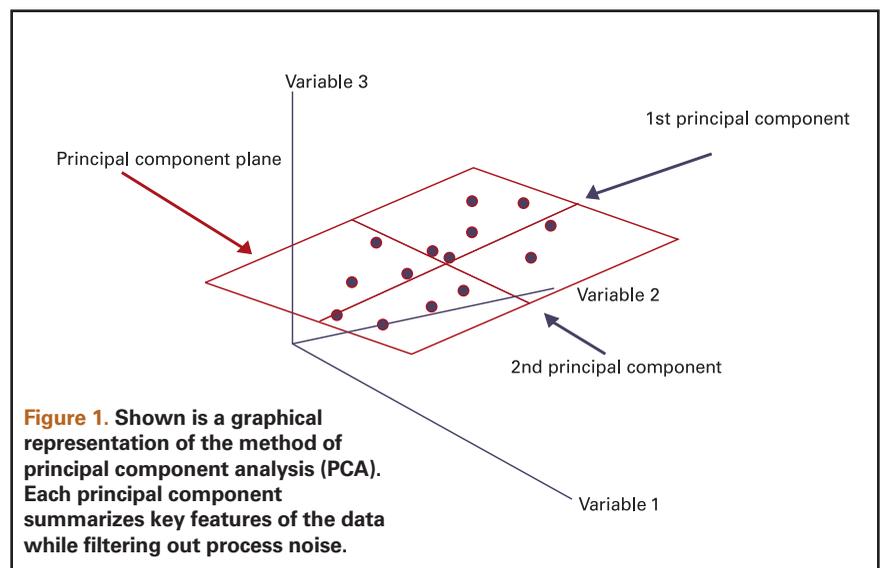
## Using multivariate process analysis to predict injection molded part quality

Molding well consistently means accounting for every factor, from resin condition and environment to the actual molding process, and the interactions among those many variables. But it can be done. Here's how.

—Daniel Hazen and David Kazmer

Maintaining consistent high-quality product in injection molding is all too often dependent on the trial-and-error refinement of handbook data and on operator adjustments that compensate for the quirks of a process. This approach is both costly and time consuming, as well as being very dependent on the expertise of the operator.

Why is quality control in injection molding such a “black art”? The answer lies in the fact that (although there may be cries of protest) IM is a poorly understood, complex process. It is influenced by multiple intrinsic and extrinsic variables that affect the final part quality, and this leads to a process that is very difficult to control.



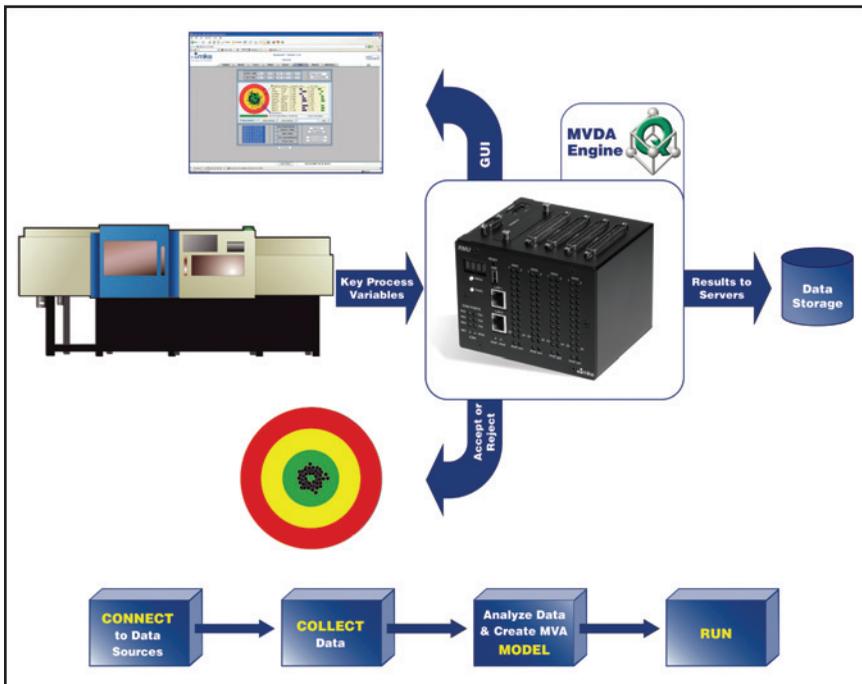
Every molding process is impacted by many sources of possible variation, so for starters we've categorized them into four groups. They are: raw material variables such as density, rheology, and molecular weight; machine variables such as barrel/screw design, mold design, screw speed, and displacement; process variables such as melt temperature and pressure, cooling rate, and flow rate through the mold; and the surrounding environment, which is easily overlooked but can influence the molding process.

Ideally, quality control in any process is maintained through strict management of each of the variables affecting product quality. In IM, howev-

er, not all of these variables can even be measured, let alone controlled; therefore, the ideal approach to QC is not possible. Alternative methods, such as the use of multivariate analysis (MVA) technology, need to be deployed.

### All together all at once

MVA technology effectively separates the signal from the noise in data sets that have many interacting variables. It presents the data in clean graphical form that simplifies large, unwieldy data sets, reducing them to simple model representations that can be easily understood and used for quality control. This approach provides much more informa-



**Figure 2.** In this real-time multivariate fault detection system for injection molding, the system connects to the process signals, collects process data, and creates multivariate models of the process.

tion about the IM process than univariate data analysis, which considers only one process variable at a time.

MVA techniques based on statistical methods can be very effective at analyzing IM processes. One such method, principal component analysis (PCA), is especially powerful at creating a succinct summary of a data set and then producing readily understood visualizations. It effectively finds the quantitative relationships that exist among all of the variables in a given process.

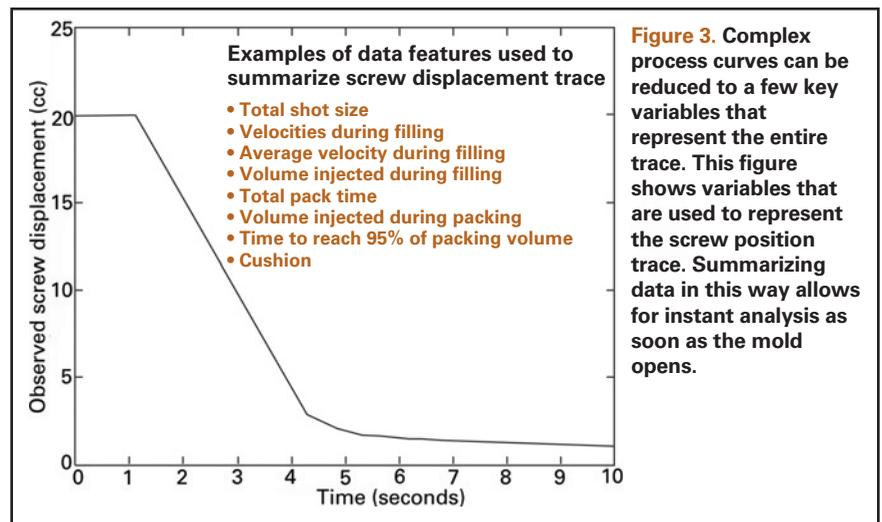
Crudely, PCA works like this: As a multivariate model is created, multiple fitting planes are generated within the data that best explain the variation and behavior of the data. In PCA, the first step is to create the first and second principal components. A line is fit to the space that best defines the data and another line is fit to the data that provides the second most detail. These are the first and second principal components, respectively. The principal component plane is fit to these lines. Each principal component plane that is created can then be analyzed (see Figure 1).

PCA can be used to develop multivariate models from historical data, effectively capturing the process characteristics. Statistics based on current data can then be tested against the historical model for quality prediction. In particular, two statistics are useful in summarizing process behavior: the DModX and Hotellings  $T^2$ . The value of DModX is an indication of the variation of any particular process cycle from the established model correlation structure,

with large values indicating significant variation. The  $T^2$  value is a summary statistic that can be used as an alarm limit compared to the normal variability described by the principal components. A large value of the Hotellings for a particular process cycle indicates that the cycle exhibited characteristics unlike the expected process behavior.

Figure 2 shows the development of a real-time MVA system, but the power of MVA is best illustrated through a real-world application—for example, a real-time quality control system for a Milacron Elektra 55-metric-ton electric molding machine. The machine is instrumented with sensors for melt pressure, screw position, barrel temperatures, melt temperature, and signals to define mold closure, filling, holding, and cooling. An MKS SenseLink QM MVA engine is used for all phases of data analysis, model building, and QC implementation. This system acquires the available signals from the process and calculates the most important features of each signal. It then creates a multivariate model with an acceptable process window, performs multivariate analysis on each cycle, and accepts or rejects the part based on this analysis. In addition, the MVA engine transmits this information to storage and auxiliary systems.

We’re going to consider two different IM applications: an easy-to-fill, low-pressure plaque molding application that uses an ABS dried at 85°C; and a more



**Figure 3.** Complex process curves can be reduced to a few key variables that represent the entire trace. This figure shows variables that are used to represent the screw position trace. Summarizing data in this way allows for instant analysis as soon as the mold opens.

difficult-to-fill, high-pressure application that uses 40% long-glass-fiber-filled PP.

MVA predictive QC is developed in three phases: sensor and signal selection, real-time MVA model development, and system validation.

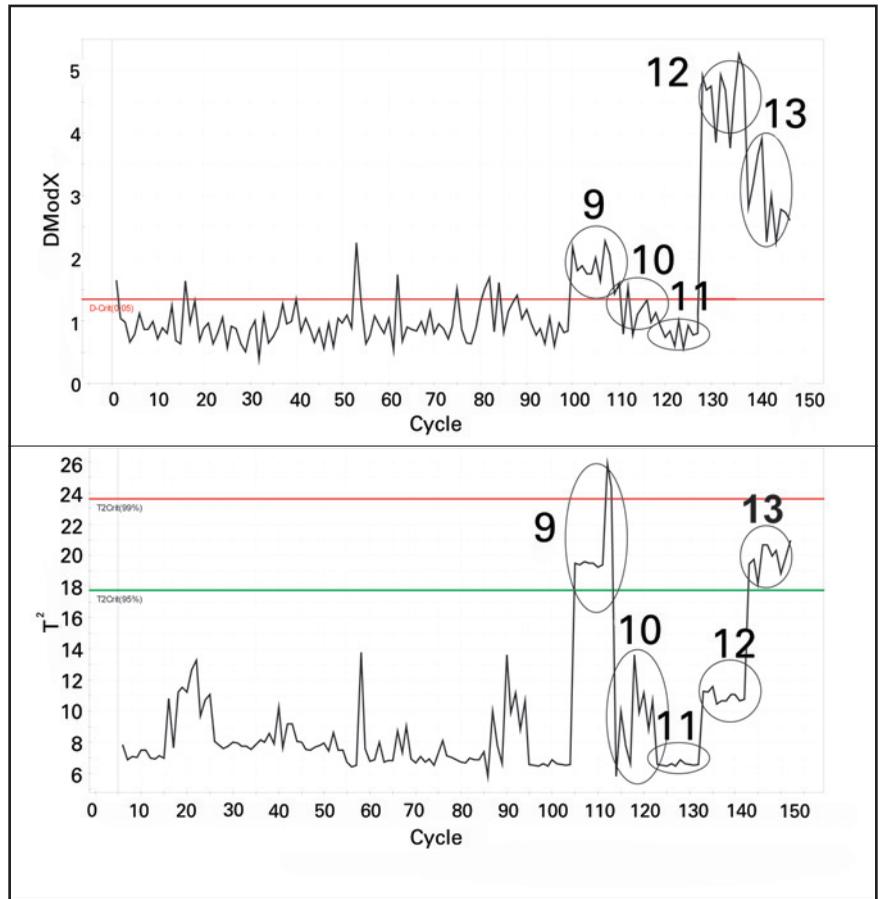
### Sensor and signal selection

In the first phase, the MVA engine analyzes the key aspects of each data signal in order to determine key data features. There are a couple of reasons for this. First, time-varying process signals contain thousands of points and these can often be summarized by only a few data features representative of the observed behavior (see Figure 3).

The second reason to define data features is that certain process states may be more evident in specific data features than they are in the raw data. Consider, for example, melt viscosity. It is a complex function of the material type, melt pressure, ram velocity, and melt temperature. Without defining representative data features that quantifiably correlate with melt viscosity, the effect of this variable can't be quantitatively expressed in the model development process.

### Real-time MVA model development

Once the signals and data features are developed, an application-specific model must be developed for quality control purposes. In our example, the stages of the molding process were defined and the key features present in each signal

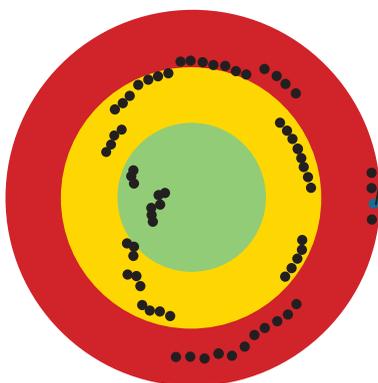


**Figure 4.** These MVA charts show the DModX and T<sup>2</sup> statistics for validation runs 9-13 where the results from these runs were compared to the model developed from the DOE (first 100 shots).

were determined from the results of a two-level, 11-factor Resolution IV design of experiments (DOE) with weight, thickness, and length of molded test plaques used as the response variables. A combination of partial least squares (PLS) and variable of importance (VIP) analyses showed that 38 out

of a total of 546 identified data features had very high statistical significance. Data features such as the screw displacement during recovery, pack time, plastication energy, screw velocity during packing, and integral of pack pressure had the highest overall importance.

In the second phase of the process the



2007-09-07_08-21-00-010		DModX=46.442		T <sup>2</sup> =421.091	
Inj. energy (J):	21,433.591	-137.959	<div style="width: 100%;"></div>	-70.943	<div style="width: 100%;"></div>
Screw displacement/filling (mm):	63.552	-27.911	<div style="width: 25%;"></div>	0.052	<div style="width: 100%;"></div>
Plastication energy (J):	-8269.767	-27.5	<div style="width: 25%;"></div>	-34.88	<div style="width: 100%;"></div>
Screw displacement/packing (mm):	13.999	27.27	<div style="width: 25%;"></div>	-0.275	<div style="width: 100%;"></div>
Max. inj. pressure/packing (bar):	426.149	25.115	<div style="width: 25%;"></div>	-0.565	<div style="width: 100%;"></div>
Avg. screw velocity/filling (mm/sec):	99.698	-19.781	<div style="width: 25%;"></div>	0.049	<div style="width: 100%;"></div>
Melt viscosity/filling (Pa-sec):	4.660	19.096	<div style="width: 25%;"></div>	-0.003	<div style="width: 100%;"></div>
Avg. inj. pressure/filling (bar):	278.252	-14.978	<div style="width: 25%;"></div>	0.44	<div style="width: 100%;"></div>
Avg. screw velocity/transfer (mm/sec):	16.587	9.952	<div style="width: 25%;"></div>	-1.706	<div style="width: 100%;"></div>
Melt viscosity/plastication (Pa-sec):	9.910	-5.638	<div style="width: 25%;"></div>	-0.071	<div style="width: 100%;"></div>

**Figure 5.** The main SenseLink control chart displays MVA results along with variable rankings detailing the main contributors to an out-of-spec process. This visual display assists in fast troubleshooting since the variable at the top of the list points to the cause of the defect.

## An analysis glossary

**Multivariate analysis (MVA):** A statistical or graphical technique that considers the relationships between multiple variables for many observations simultaneously.

**Principal component analysis (PCA):**

Technique used to reduce the dimensionality of a data set and to summarize the most important aspects of the data, while simultaneously filtering out noise. (A detailed description of the origins and workings of PCA can be found at [www.umetrics.com/default.asp/pagename/methods\\_MVA\\_intro/c/1.1](http://www.umetrics.com/default.asp/pagename/methods_MVA_intro/c/1.1))

**DModX:** The distance from the observation to the model plane, also known as

the residual error.

**Hotellings T<sup>2</sup>:** The normalized distance of the observation to the projected model center.

**Design of experiments (DOE):** A structured, organized method for determining relationships between factors that affect the process or the responses of the system.

**Partial least squares or projection to latent structures (PLS):** A generalized multiple regression method that can handle multiple collinear X and Y variables.

**Variable of importance (VIP):** The calculated influence on all the Y variables from all the X terms in the model.

most important data features defined by the first phase are analyzed to create the best multivariate model of the process. In our example, a fractional factorial, fully saturated DOE with seven variables was developed. The design used factor limits to guarantee that 100% acceptable parts would be produced in each run of the design matrix. Mass, thickness, length, and width of the molded part along with flash and short shot were used as response variables. A multivariate PCA model was created from the results of this DOE. For the low-pressure molding application, the model explained 99.8% of the variation in the data features. Similar analyses of the high-pressure data yielded a model that explained 99.7% of the variation. The limits for DModX and Hotellings were automatically generated for these models using the multivariate analysis within the MVA engine.

### Control system validation

After the MVA model was developed, validation runs were performed with

some of the molding factors intentionally set so the DModX and Hotellings T<sup>2</sup> statistics would fall outside of the control limits. Figures 4 and 5 show DModX and T<sup>2</sup> statistics for the low-pressure molding process.

Analysis of the quality data showed that parts from runs 10 and 11 were OK while those from runs 9 and 12 had flash and parts from run 13 suffered short shots. The analysis of all of the data gathered and analyzed in phase two of the MVA QC development process showed that for low-pressure molding, 80% of the part quality could be predicted each by T<sup>2</sup> and DModX, while 100% was accurately predicted by a combination of both. For high-pressure molding, 100% of the part quality was predicted each by T<sup>2</sup> and DModX.

The user interface within the MVA engine system provides a clear radar screen that plots DModX and T<sup>2</sup> for each shot of data in real time. Figure 5 shows this screen for different DOE and validation run settings. Each of the

defective validation runs resulted in data in the red area, while data from the DOE and from the acceptable validation trials produced data in the green and yellow zones. Data points can be selected and contribution plots can be displayed that detail the variation in the DModX and T<sup>2</sup> values and the root variable cause for the variation in MVA statistics. Figure 5 shows the analysis and contribution plot for a single cycle, where the injection energy, followed by the screw displacement during mold filling, was the main contributor to that cycle varying outside of the model limits.

It has been relatively straightforward to use the MVA engine to remove the “black art” from the development and implementation of a very effective QC system in our IM process. The data feature sets that are employed by this engine for process analysis are a powerful means of representing the material, machine settings, and part quality attributes within the process. In our example, the analysis of the data features quickly and easily determined the most important variables in the molding process and the relationships between all the process variables. More importantly, once validated, the MVA system for predictive QC in injection molding was 100% accurate in the rejection of visually defective parts online.

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