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Rubber Injection Molding with Quality Recognition

Automatic Process Monitoring with iQ Clamp Control and Machine Learning

With the increasing digitalization of injection molding, new process parameters are coming under the spotlight. Engel, together with the Polymer Competence Center Leoben and Montan University Leoben, Austria, is using machine-learning methods to explore the potential of mold breathing for quality assurance in rubber injection molding. This research project was supported by the partner company SKF Sealing Solutions Austria.

The collection and interpretation of process data supports producers of safety-relevant rubber products in ensuring a constant high quality © iStock

Technical rubber products, such as gaskets, dampers or connectors, are critical in many applications for the proper and reliable operation of systems, equipment or vehicles. Nevertheless, economic and environmental factors are forcing manufacturers to integrate ever more functions into their components with ever lower resource consumption [1, 2]. Here, manufacturers are supported in continuing to ensure a constantly high quality by the collection and interpretation of process data [3–5].

The iQ clamp control assistance system of Engel Austria GmbH with mold breathing, provides a useful signal that enables automatic clamping force optimization. It also facilitates monitoring of the production process and manual optimization of quality-relevant parameters, such as changeover point and holding pressure time. It was developed for processing thermoplastics, where it is already widely used [6, 7].

As part of a scientific study, the system was evaluated for elastomers. Chemical crosslinking poses a challenge for this application. The goal of trials by the project partners, Engel, Polymer Competence Center Leoben (PCCL) and Montan University Leoben (MUL), was to detect critical process deviations in the manufacture of rubber parts in real time using the mold breathing signal to detect parts out of tolerance already during the manufacturing process without an additional manual quality control step. To simulate process deviations, the mold temperature was deliberately increased during injection molding without adjusting the crosslinking time accordingly. This causes an impermissible change in the dynamic-mechanical properties of the parts, equivalent to producing rejects as a result of process disturbances.

The process monitoring is performed with the aid of PCA-based methods (principal component analysis). These are machine-learning methods and are capable of utilizing clear correlations between different process signals – e.g. mold breathing (**Fig. 1**). This allows the error identification rate to be significantly improved compared to standard methods, and temperature-related process disturbances to be visualized.

To allow the PCA, and therefore the correlation between the process and quality data in the production process, to be performed, a training dataset must be generated from the process data for acceptable parts. This training set, which is used as a basis for the subsequent inline error identification, is determined experimentally.

Trainings Set as a Basis for Subsequent Inline Error Identification

The tests were performed in Engel's technical center on an e-victory 740/220 injection molding machine with a maximum clamping force of 2200 kN. For the mold temperature control, heating platens with electrical heating elements were used, of which the setpoint values could be changed by controlling the injection molding machine. A carbon black-filled nitrile-butadiene rubber (NBR, manufacturer: SKF Sealing Solutions Austria) that is typical for industrial applications was processed into sample parts. In preliminary tests, settings were found for all process parameters, which ensure a stable part production process (**Table 1**). The heating time was chosen so that, at the point of demolding at a mold temperature of 160 °C, the parts have a degree of crosslinking of 90 %.

The settings were kept constant over 20 cycles, in order to generate training data in cycles 5 to 15 after a short transient oscillation. A constant temperature of 163 °C was established, which was measured with the mold temperature sensor (**Fig. 2**). From cycle 21, the setpoint value of the heating elements was increased to 180 °C, causing the measured maximum mold temperature also to rise. From cycle 52, the control temperature of the heating elements is reduced to 160 °C again.

With the increase of the setpoint temperature, unexpected temperature deviations resulting from possible malfunctions of the heating or thermal elements were simulated. On this basis, the threshold value for impermissible changes of part quality, as well as the response behavior of the process monitoring methods, were investigated.

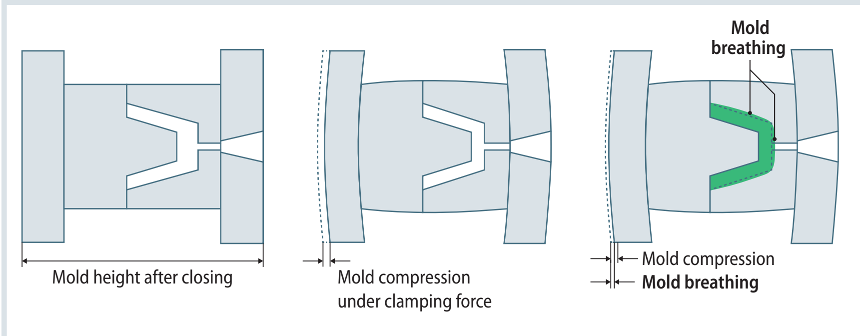

Fig. 1. Mold breathing: The mold is compressed by the build-up of the clamping force. During filling, the resulting part generates an opening force, which is counteracted by the compression. The opening force is proportional to the cavity pressure and to the projected surface area

Source: Engel; graphic: © Hanser

Determining Dynamic Material Behavior

The dynamic-mechanical properties of the parts are investigated with an electrodynamic test system, type Instron ElectroPuls E3000 (manufacturer: Illinois Tool Works). The test method used can determine the characteristic material behavior in the pressure oscillating load range. The material's response to the introduced load is determined as a characteristic value of the tangent of the loss angle tan(δ), which describes the ratio between plastic and elastic material behavior. It thereby provides useful information about the degree of crosslinking.

The tan(δ) values determined in the dynamic tests, as expected, correlate during the test with the measured mold temperature from **Figure 2**. An increase of tan(δ) means an increase of the plastic components, e.g. because of a lower degree of crosslinking under the changed crosslinking conditions (**Fig. 3a**).

Parameter	Setpoint value
Cylinder temperature [°C]	80
Screw speed during metering [ms^{-1}]	0.16
Backpressure [bar]	150
Injection volume flow rate [cm^3s^{-1}]	10
Holding pressure [bar]	350
Holding pressure duration [s]	35
Heating time [s]	300

Table 1. In preliminary tests, settings ensuring a stable manufacturing process were found for all process parameters. These parameters were held constant in all experiments Source: PCCL

In the training phase (cycles 5 to 15), tan(δ) has a mean value of 0.209, with a standard deviation (σ) of 0.002. Starting from this, a tolerance range of ±3 σ is defined. If a part has a value outside this range, it is to be considered an unacceptable part. In the time sequence of the test cycles, this range is left as from cycle 23 and only consistently reached again with cycle 58. The object of statistical process monitoring systems – in this case PCA – is now, while the process is running, to use the process parameters to identify whether the part quality lies within the permissible process window. For assessing the investigated monitoring methods, the individual cycles were marked as acceptable or unacceptable parts corresponding to the marked control limits.

Correlation between Mold Breathing and Cavity Pressure

To confirm that mold breathing is suitable for error recognition, the correlation between the breathing signal and the cavity pressure was first investigated in practical tests (**Fig. 4**). It is conspicuous that the mold breathing signal only shows significant deflections when the mold is almost full, while the cavity pressure rises as soon as the flow front reaches the sensor (**Fig. 4a**).

This behavior can be expected since, besides the pressure, mold breathing also takes into account the projected, already filled surface area. At the switchover point, on the other hand, the peaks of both signals are equally pronounced and can therefore be exactly evaluated. If the peaks of the two signals for all cycles are »

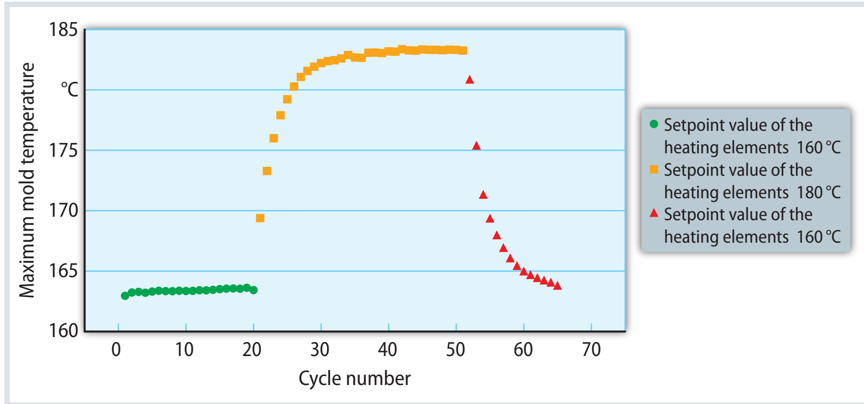

Fig. 2. The maximum mold temperature at the cycle end follows immediately after the setpoint values of the heating elements Source: PCCL; graphic: © Hanser

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plotted one on top of the other (**Fig. 4b**), a linear relationship can be clearly seen.

Process Monitoring with Principal Component Analysis

Processes with multiple variables can be suitably monitored using multivariate statistical methods [8, 9]. For the tests, a PCA-based approach (**Info Box**) was chosen to reliably identify process fluctuations, and therefore quality fluctuations. The recorded process variables, with the exception of the mold temperature, are then processed by principal component analysis, and the SPE (squared predictive error) statistics for each test cycle are computed (**Fig. 3b**). Cycles 5 to 15 were used as training data. A common, unilateral intervention limit is calculated from these using the PCA method. If the SPE statistics of a cycle lie beyond this limit, the part is identified as probably unacceptable. Here, the common evaluation of the process variables is found to make the change in mold temperature visible in a statistically significant way, without the need to measure it directly. The change of mold temperature is rapidly identified; only from cycle 55 does the system return to normal operation.

The correct classification rate, i.e. the proportion of cycles that are in each case correctly assigned to acceptable or unacceptable parts, is 85% in these experiments. The basis for decision-making here lies in the violation of the tan(δ)) intervention limits. The 15% incorrect classifications are all cycles that ought to be unacceptable parts according to PCA, but are acceptable parts according to tan(δ). The monitoring system would thus be oversensitive. However, the incorrectly classified unacceptable parts are underlain by critical process deviations that are correctly recognized by the system and do not have an impact on the quality feature tan(δ) that is specifically investigated, but can bring other quality features out of tolerance.

All the incorrectly classified data are identified with hollow markers (**Fig. 3**). The process monitoring system thus classifies cycles 3 and 4 as errors (**Fig. 3a**), which can be attributed to process conditions at the start of the test that have clearly not yet settled to the steady state. Despite the return to normal process conditions from cycle 51, the dynamic properties of the parts only lie within the control limits again after a delay. It is conspicuous that cycles 60 and 62 are qualified as unacceptable parts, although the measured mold temperature is already in the range of normal conditions again at 160 °C. The system thus also responds to other process disturbances. A comparison with **Figure 3b** shows that exactly these two cycles have higher tan(δ) values than adjacent cycles.

Something similar can be seen with cycle 23, the tan(δ) value of which is lower than that of the adjacent cycles, and also the SPE statistics lie below the intervention limit. Also in the case of acceptable parts, there seems to be a certain relationship between the SPE statistics and part quality according to tan(δ).

In general, the examples show that despite a strong correlation, none of the evaluated process signals is able to represent the crosslinking process absolutely. All the variables recorded in the experiments describe changes of physical properties of the rubber, especially the flow behavior. However, if the prop-

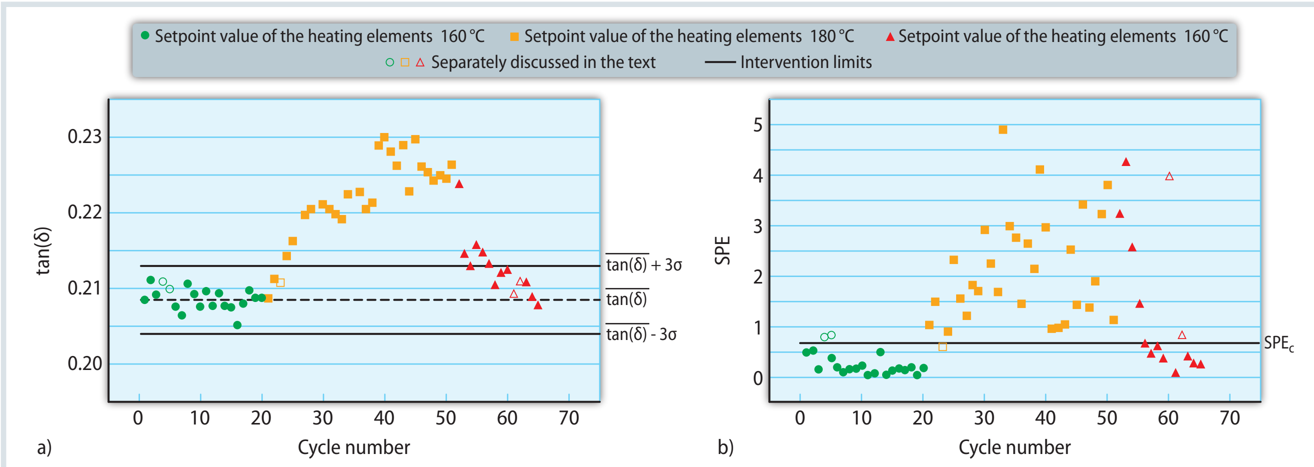

Fig. 3. The tan(δ) values of the elastomer parts are strongly influenced by the mold temperature (left). SPE statistics allow changes in the process conditions potentially leading to rejects to be recognized (right) [9] Source: PCCL; graphic: © Hanser

erties of the chemical crosslinking are not in a linear relationship with the physical, the part properties that are primarily determined by the degree of crosslinking cannot be clearly predicted. If all the process signals as well as the multivariate monitoring indicate that the flow properties have changed, even if the predicted tan(δ), which is determined principally by the curing reaction, lies within the intervention limits, then detailed part checking should be performed. Only then can it be assessed whether the unexpected process fluctuations are uncritical or whether they lead to rejects.

Summary

Based on the iQ clamp control intelligent assistance system, it was possible, using principal component analysis, to set up a multivariate process monitoring system for rubber injection molding that immediately identifies changes in the process conditions, and classifies the corresponding molded parts as unacceptable. The advantages of this system lie in the low training effort and the possibility of simultaneously processing multiple process variables. Additional information about the significantly better performance compared with standard methods can be requested from the authors. The challenge in elastomer injection molding consists in the fact that most available process signals correlate strongly with the flow properties of the materials, however only weakly with the chemical reactivity, which further sets limits on process signal-based fault identification. The system developed by Engel, PCCL and MUL shows trends in process fluctuations even before they have affected the part quality. This opens up great potential for optimizing series processes in the rubber-processing industry. ■

PCA Principal Component Analysis

Principal component analysis is a dimensionality reduction method for increasing the defect recognition rate during process monitoring. At the same time, the complexity can also be reduced. Its particular suitability for industrial processes lies in the fact that it can eliminate linear dependencies between process signals. More detailed insights into the methodology and other application reports can be found in Russel, Chiang et al., Yang, Chen, et. al. and others [4, 10–13].

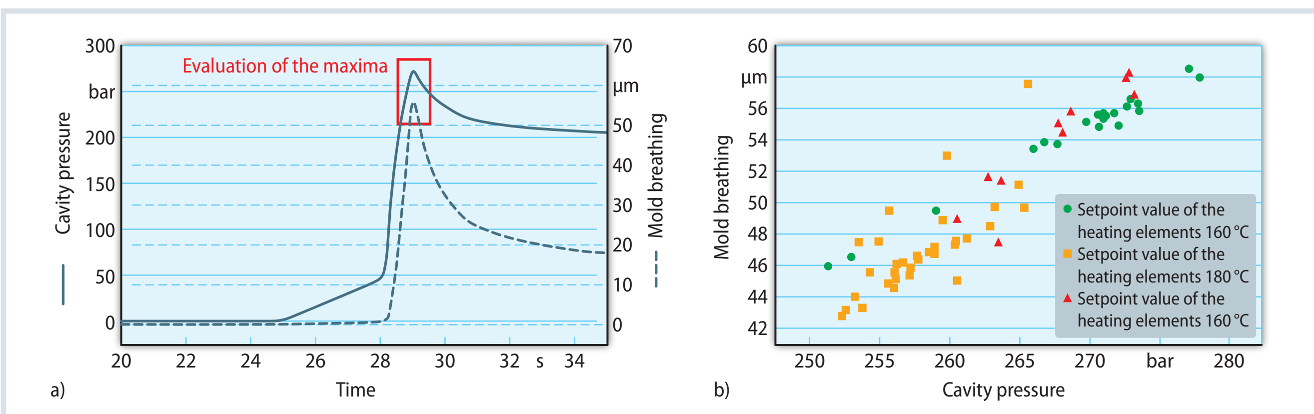

Fig. 4. Mold breathing responds with a delay compared to the cavity pressure, but then simultaneously reaches a pronounced peak (left). Maxima of mold breathing and cavity pressure are strongly positively correlated (right) Source: PCCL; graphic: © Hanser