Advanced Data Acquisition and Analysis for Injection Molders

Stefan Kruppa¹, Reinhard Schiffers¹, Matthias Busl¹, Ulrich Lettau²
¹KraussMaffei Technologies GmbH, Munich, Germany; ²iba AG, Fürth, Germany

Abstract

The subject of this publication is the detection of optimization potential and the avoidance of faults and errors in the injection molding process using process data analysis. In modern injection molding machines, in addition to the produced plastic moldings, high amounts of process and machine data are available – in very high quality. Injection molding machines are equipped with high-resolution measuring devices that are connected to the bus system of the machine, which reaches out to all the components from the plasticizing barrel, frequency converters for drives, mold cavities, etc. To date, however, these data have not been fully exploited and have not been accessible in a convenient way. Through the further development of bus-based data interfaces, it is now possible to obtain all signals and sensor data, and use these data for external analysis purposes. The decisive factor is central recording of the relevant signals with a uniform time base. Corresponding recording in real-time facilitates complete documentation and utilization of the relevant process and machine data. Subsequently, these raw data must be processed appropriately so that they can be used for analysis purposes in order to extract the information from process and production, and generate corresponding benefits for the users and operators. Firstly, strategies and methods are shown on how (raw) data from a machine control (PLC) can be extracted and made available to the operator. For a diagnostically conclusive analysis, the complexity and the size of the data must be significantly reduced – here, machine and process-specific key figures are generated. Key figures are combined with one another and further compacted so that additional information can be obtained more easily (Figure 1).

Introduction

In the plastics processing industry, there is often a high degree of specialization and enormous production depth within the branches. This is due to a market that is becoming increasingly sophisticated as more and more complex components are possible due to material innovation or process combination. In most cases, complex components also require complex manufacturing processes, which must be mastered, above all, technically. Nevertheless, efficient and economical production is required. Thus, the production of high-quality and critical-use injection-molded products requires precise monitoring of the manufacturing process to maintain a repeatable process. Often, an initially stable process is disturbed by (random) influences and fail parts are produced [1]. Modified input conditions also require re-adjustment of the initial process settings [2], [3]. The machine operator is already provided with a wide range of parameters and tools to monitor the injection molding process [4]. Nevertheless, the injection molding process may be a black box for external observers as there is no chance to observe the processes inside the machine or the mold [5]. Curve plots and trend graphs visualize changes and enable the production history to be viewed. However, in order to be able to comprehensively analyze the injection molding process, tools (outside the injection molding machine) are required, which allow a deeper insight into the process. Expert knowledge permits interpretation of the curves of pressure and position signals from sensors or directly from the drives of the individual motion axes. It is necessary to translate corresponding expert knowledge individually, e.g. into key figures and evaluation specifications, to enable simpler and more robust operation of injection molding machines.

Data Collection and Recording

The tests were conducted with a DX 512 DataXplorer from KraussMaffei Technologies GmbH, Munich (optional available) for its injection molding machines. This means that a maximum of 512 predefined signals (analog I/Os, frequency converters, bus-based signals, etc.) can be recorded in a file based ring memory on the integrated SSD (the recording capacity depends on the used hard drive; for this purpose, a 128 GB unit was used). The analysis was conducted with the software ibaAnalyzer (iba AG, Fürth, Germany), which provides...
powerful mathematical and technological functions for processing, combining, calculating and generating signals\cite{6,7}. Table 1 shows an extract of the recorded process parameters and trigger signals.

**Table 1: Signal list of recorded data (excerpt)**

<table>
<thead>
<tr>
<th>digital signals</th>
<th>analog signals</th>
</tr>
</thead>
<tbody>
<tr>
<td>new cycle</td>
<td>injection_pressure</td>
</tr>
<tr>
<td>cycle running</td>
<td>Injection_velocity</td>
</tr>
<tr>
<td>clamp closing</td>
<td>plasticizing_rpm</td>
</tr>
<tr>
<td>clamp open</td>
<td>screw_position</td>
</tr>
<tr>
<td>Injection</td>
<td>cavity_pressure</td>
</tr>
<tr>
<td>Holding</td>
<td>clamp_velocity</td>
</tr>
<tr>
<td>Plasticizing</td>
<td>clamp_position</td>
</tr>
<tr>
<td>decompression_1</td>
<td>clamp_force</td>
</tr>
<tr>
<td>decompression_2</td>
<td>clamp_cushion_pos</td>
</tr>
<tr>
<td>Cooling</td>
<td>ejector_position</td>
</tr>
<tr>
<td>Clampforce</td>
<td>ejector_velocity</td>
</tr>
<tr>
<td>Ejection</td>
<td>injection_heating_temp</td>
</tr>
<tr>
<td>turntable_turn</td>
<td>mold_heating_temp</td>
</tr>
<tr>
<td>sliding_table_open</td>
<td>water_battery_temp</td>
</tr>
<tr>
<td>cascade_open</td>
<td>oil_temp</td>
</tr>
<tr>
<td>cascade_close</td>
<td>energy_total</td>
</tr>
<tr>
<td>core_out</td>
<td>accu_pressure</td>
</tr>
<tr>
<td>core_in</td>
<td>pump_pressure</td>
</tr>
</tbody>
</table>

Because of the integration of the sensors installed in injection molding production cells, a large amount of measurement data are recorded, which can be evaluated regarding the process itself. Injection molding machines have, for example, a data connection to the frequency converters of the drives, to the amplifiers of temperature and cavity pressure units, if connected to the machine. This allows continuous recording of torque and pressure profiles, as well as flow rates and temperatures of the cooling liquids. If the quality data of the produced parts are also acquired, the process data can be correspondingly (model based) correlated with the product quality\cite{8,9}.

**Data Analysis: Graph interpretation**

Although injection molding is largely automated, the human factor is not to be underestimated. In the setup process, it is important to find a stable process window, e.g. a robust operating point, to prevent a fault-prone process. In order to identify faults or deviations in the process, (visual) representation of the individual physical parameters such as pressures, positions or even temperatures is required. By storing the data in a cycle-specific manner, conclusions can be drawn about an individual process state. The overall picture of the individual process curves describes the currently prevailing process state – it forms, so to speak, the fingerprint of the process. This process state can thus be stored, recalled and transmitted. Thus, two objectives are pursued: the availability of production facilities is increased by the early detection of disturbances and the quality of the production process can be tracked and optimized over the entire process chain. Changes in the input variables and the production conditions are inevitable and require effective compensation. By accessing all historical process data, it is possible to compare a current process with one from the past. Up to now, for example, only parameterization parameters are noted in mold validations, but reproducing the same molding quality is only possible with difficulty, especially if the mold is to be used on another machine. Almost all process variables are mutually dependent. If, for example, the back pressure is reduced in the dosing phase, this also has direct influences on the mold filling phase. One possible consequence is reduced injection pressure. The interaction between the parameters allows conclusions to be drawn on the process window.

An operator is, however, often unaware of the circumstances or connections, and correlation and visualization on the machine itself are too complex. It requires detailed analysis to detect errors and optimize sensitive processes. The data allows the users to completely understand what is happening during each stage of the injection molding process. The conventional injection molding production process can be divided into various cycle sections which can each be assigned to a corresponding trigger. Depending on the process phase, individual signals are relevant for an evaluation. Signals such as the closing position or speed are important for process phases that contain mold movements. In the dosing phase, the torque of the plasticizing drive and the back pressure are often required, and the screw position and the cavity pressure are required in the injection phase. Various signals also find redundant uses.

**Use case 1: Heating check for start-up**

During the initial heating phase of an injection molding machine, the heating tapes and cartridges are heated by electrical nozzle, barrel and mold heating to ensure the required operating temperature. The heating phase is pre-molding. All temperatures must be on set point and stable to also achieve a stable process. Figure 3 shows regular behavior. Nevertheless, the curves are helpful for debugging and can be used to identify defective heating elements or errors in controller programming by comparing and interpreting the heating curves on the graph. This
enables control parameters to be adjusted and weaknesses to be identified and corrected.

Figure 3: Graph for barrel, nozzle and mold temperature for the initial heating process of an injection molding machine (KM 160-540 PX).

Use case 2: Metering torque monitoring
If the relevant process data on the injection molding machine are recorded and evaluated according to the requirements, changes in the process can be detected online. Figure 4 shows the curves of the metering torque of the plasticizer drive and the screw position for processing of polypropylene with the MFI 6, 11 and 19 (SABIC PP 571, 575 and 576, KM 100-380 AX). Changing viscosities can be correspondingly detected.

Figure 4: The set back pressure of 50 bar is closed loop controlled during plasticizing. A plasticizing speed is also set. Differences in the processing viscosity result in different metering torques $M_{\text{plst}}$[10].

Use case 3: Check-valve closing detection
A statement about the closing time of the check-valve (which prevents the melt backflow during injection and holding phase) can be made via an evaluation of the torque signal profile (Figure 5). In general, the rotary movement of the screw is blocked during the translatory injection movement. In the case of hydraulically driven injection molding machines, this takes place by blocking the oil flow via the valve on the hydro-motor. For electromechanically driven injection molding machines, this is carried out via the plasticizing drive which prevents the plasticizing screw from rotating through positioning control [11]. Leakage of the check-valve can thus be quantified by measuring the holding torque of the screw.

Figure 5: Torque curves for the plasticizing drive in the injection phase for 20 successive injection molding cycles (PA6, KM 100-380 AX). Melt flows back into the screw flights during the closing phase of the check-valve, thus producing a torque. Non-uniform closing of the check-valve results in different characteristics of the torque curve.

Use case 4: Oven temperature monitoring
During the molding or shaping process of fiber-reinforced organic sheet inlays, attainment of a specific heating temperature is very important. Before a sheet is inserted into a mold, it must be heated in an (infrared) oven to melt the polymer matrix accordingly and to enable a connection between the matrix of the sheet and the injected polymer melt.

Figure 6: Temperature plot for 3 individual successive heating processes (KM 300-1400 CX FiberForm). The pyrometer installed in the oven is connected to the control unit of the machine.

Figure 6 shows a temperature curve plot for 3 individual successive heating cycles. The temperature signal is measured via a pyrometer installed inside the oven aiming
directly on the surface of the sheet. On the one hand, the exact heating process can be monitored and documented in detail; on the other hand, key figures such as maximum or average heating temperature can be calculated with corresponding trigger signals. Generation and monitoring of a tolerance range are also useful to detect deviations and/or anomalies in the heating process.

**Data Analysis: (custom) key figures**

In use cases 1 to 4 it was shown how graphical interpretation of the raw data time series can lead to process insight. Once process deviations and anomalies can be visualized and explained in the raw data, it is possible to define process indicators or key figures that describe a specific process property. A key figure is calculated by aggregating the information of one or more signals recorded during one cycle with mathematical methods. This is carried out periodically after each cycle has been completed, thus giving one set of meaningful key figures per cycle.

Key figures can largely vary due to material-, process- or machine-induced influences. Therefore, it is very important to identify and quantify regular influential factors. Key figures can then be filtered and classified according to these factors. Hence, the filtered key figures can be visualized as a long-term trend and evaluated with statistical methods. Faults and irregular changes in the process can thus be detected and assigned to individual root causes. Process variables such as forces on the screw shaft, mold cavity pressure, temperatures, screw position or injection speed can be displayed in curve plots. Key figures such as maximum melt pressure or cavity pressure, plasticizing time or average barrel and mold temperatures are calculated and displayed for each injection molding cycle. In this way, creeping changes can also be detected by considering the historical development of the parameters. Complex processes and special processes require tailor-made key figures which are not available in controls of injection molding machines since they are to individual and thus unsuitable for the standard of the control unit.

**Use case 5: Cooling time monitoring**

Dynamic mold temperature control technologies that rapidly raise the mold wall temperature during the mold-filling stage make it possible to improve flow lengths, reduce internal part stress and attain high quality surfaces. However, cycling the mold temperature calls for exact monitoring of heating and cooling time to maintain high process and product quality. Figure 7 shows a plot of the custom tailored key figure cooling time \( t_{\text{cool}} \).

\[
\text{Figure 7: Cooling time plot conducted on an all-electric injection molding machine (KM 200-540 PX) with dynamic-mold-heating (DMH) for two days.}
\]

\[
\begin{align*}
\text{Use case 6: Cycle time robustness} \\
\text{The robustness of the process is determined by the weakest link in the chain. To identify and remedy weaknesses, a cycle time fluctuation analysis may be useful. The duration of the relevant cycle sections is measured. A standard deviation } \sigma \text{ is calculated for every section (in Figure 8a over 500 cycles). The most fluctuating section indicates where to start in order to increase process robustness and stability. As a monitoring figure, the standard deviation can be calculated as a moving standard deviation on, for example, the last 10 cycles (compare Figure 8b). In this way a key figure is created that can be monitored for changes and is completely independent of the process.}
\end{align*}
\]

\[
\text{Figure 8: Time fluctuations for 500 cycles for an all-electric machine (KM 120-540 PX), standard deviation } \sigma \text{ comprising 2500 cycles for: injection, cooling, opening, closing and pause time (a). Moving standard deviation for the last 10 cycles (b).}
\]

\[
\begin{align*}
\text{Use case 8: Plasticizing linearity} \\
\text{In addition to the process-specific key figures, expert knowledge and best practice examples can be transformed into algorithms that can be used to monitor all injection}
\end{align*}
\]
molding machines. This procedure is shown here using the key figure "plasticizing linearity". During the plasticizing process, the screw is pushed back by the plastic mass, with a speed depending on rotational screw speed and set back pressure. This process essentially determines the homogeneity of the melt and thus the injection process and part quality. An empirical evaluation measure for the quality of the plasticizing process is the linearity of the screw retraction speed or the course of the screw position during plasticizing. If this curve is a straight line (see the red dashed line in Figure 9), the process was uniform and the dosed plastic mass was therefore homogeneous. Disturbances can occur in various forms and lead to uneven movement and inhomogeneous melt (see blue line in Figure 9). Causes for this may include feeding problems, material separation / coating or screw wear.

![Figure 9: Comparison of the real and ideal course of the screw position x during plasticization over time t.](image)

The purpose of this key figure is to express the similarity of the measured screw position signal to an ideal, linear curve. The result should be comparable and easy to interpret. The screw position is considered from 10% of the plasticizing stroke (P1) to 90% (P2) to eliminate acceleration and deceleration effects. Between these two points the ideal (linear) course and the real course are now compared. The triangular area \( A_{\text{ideal}} \) under the ideal straight line is calculated as:

\[
A_{\text{ideal}} = \int_{t_{P1}}^{t_{P2}} [x_{\text{ideal}}(t) - x_1] dt \quad (2)
\]

The area \( A_{\text{error}} \) between the two curves, that is the error area, is given by:

\[
A_{\text{error}} = \int_{t_{P1}}^{t_{P2}} |x_{\text{ideal}}(t) - x_{\text{real}}(t)| dt \quad (3)
\]

From these two surfaces, a ratio can now be calculated which indicates the correspondence between the straight line and the curve of the screw position:

\[
L = \frac{A_{\text{ideal}} - A_{\text{error}}}{A_{\text{ideal}}} \cdot 100\% \quad (4)
\]

With this value, deviations from an ideal, uniform plasticizing process can be recognized at a glance. The calculation is independent of the plasticizing time and the result is easy to interpret. The key figure is applied to a KraussMaffei 300-1400 CX machine processing Durethan PA 66 in the example depicted in Figure 10. The data show a material shortage that is resolved before the machine stopped. The nearly perfect straight curve of the first two cycles flattens in cycle 7397 due to the missing material. The following curve has the longest plasticizing time, but is already bending upwards due to incoming new material. In the last two curves the screw flights are filled again and the process is on the way back to normal operation. These events described here are captured in the plasticizing linearity figures shown in Figure 10b.

![Figure 10: Screw position for plasticizing phase conducted with a KM 300-1400 CX during material shortage (a). Plasticizing linearity in [%] (b).](image)

The plasticizing linearity for three processes is compared in Figure 11. The lowest values and the most fluctuation where measured on a KraussMaffei 200-540 PX machine processing ABS 4134 – Recycling material. This can be explained by the variability that is inherent to recycled plastics. The second-best linearity is found in the process on a hydraulic KraussMaffei 300-1400 CX machine with Durethan PA 66. This nearly perfect result is only surpassed by an electric KraussMaffei 120-540 PX machine that processes the acrylic-based multipolymer CYROLITE® GS 90. The plasticizing linearity can therefore be used as a process-independent key figure to quantify the quality of the plasticizing process. Differences between
As can be seen, plasticizing linearity of modern machines is very good. In addition, values lower than 50% are hardly conceivable and a detailed distinction is not necessary here. To obtain an easy-to-evaluate key figure, it is useful to specify the result in a logarithmic scale:

\[ L_{\text{log}} = \frac{100^C - 1}{100 - 1} \cdot 100\% \]  

One recent investigation field concerns the causes of "non-linearities". The question arises as to whether a worn plasticizing screw can be detected by examining the screw retracting curve, for example. One other point is the extension of the calculation to plasticizing processes with a speed and / or pressure profile.

Conclusions

The requirements for the quality of injection-molded parts have to be monitored by means of intelligent solutions for process control in order to be able to reduce the cost of injection molding production. The currently available options for monitoring and visualization of process data can be used with appropriate know-how for quality control and process optimization. Due to the multitude of quality requirements, there will probably be no general solution for the compensation of disturbances in the near future. However, the current approaches offer flexible ways to address the process and the specific requirements. Targeted in-line detection of faults in the process is already possible today as support for quality control. The future challenge will be to make more and more information available to the machine operator – one approach is to integrate corresponding auxiliary functions into the control of the machines. The possibilities for analyzing data present new challenges such as data management and storage. For safety-relevant components, e.g. in the automotive and medical sectors, new approaches for track and trace strategies are already emerging and are providing support, for example during a product recall or other quality issues.

References

1. J. Wortberg, Qualitätssicherung in der Kunststoffverarbeitung: Rohstoff-, Prozeß- und Produktqualität, Hanser, 1996
3. S. Kruppa, Adaptive process control and alternative injection concepts for thermoplastic injection molding, Univ. Duisburg-Essen, Diss., 2015
7. U. Lettau, Condition monitoring of plants and process analysis with a single system, Metallurgical Plant and Technology International, 2013, 34, No. 1, p. 56
10. G. Holzinger, S. Kruppa, In Situ Characterization of Polymer Melt and Molded Part Quality, SPE China Medical Plastics and Injection Molding Conference, Society of Plastics Engineers (SPE), Shanghai, China, 2013