On the Way to the Smart Injection Molding Factory

Part 2 of the Series: Integrated Data Acquisition for the Injection Molding Production

Everyone is talking about digitalization and Industry 4.0. In practice, however, implementation is often difficult. The data-driven operation of an injection molding production is often still a dream. Only if the exact actual condition of the machines and peripheral equipment is known, work on optimizing the processes can be done. The Eastern Switzerland University of Applied Sciences describes the challenges that have to be overcome and shows possible solutions based on a self-operated manufacturing cell.

Fully automated manufacturing cell for the production of a floorball at IWK's technical laboratory in Rapperswil, Switzerland © OST – Eastern Switzerland University of Applied Sciences

There are two main challenges in implementing Industry 4.0 today [1].

On the one hand, there is often a lack of awareness in practice, both for possible applications and for the necessity of a concrete step-by-step implementation. We are talking about the actual target orientation or also use case definition for the smart factory. This concretization must be oriented to the following questions:

- How can I increase my value creation by using data?
- How can I use my data? What is the goal?
- What data do I need to implement a specific use case?

The awareness for possible applications can be created by the use case framework presented in the last article of this series (***Kunststoffe** international* 7/21). This framework was systematized and developed on the basis of realized use cases in practice [2].

On the other hand, learning from data requires a complete database. Some questions arise here as well:

- Which signals do I need? Which signals are available at all?
- What quality of data do I need? Is the data available in this required quality?
- How do I get the data out of my machine?

- How do I synchronize data from different machines and devices?

The database is often a major hurdle, as the data is simply not available or not in sufficient quality. In the field of plastics processing, for example, there are no suitable, industry-wide standardized specifications and protocols that can be integrated with a variety of different data sources and database systems without any problems. This lack of standardization has resulted in each machine providing data differently today. Fortunately, many standards and specifications are currently in development (e.g. OPC UA), so interoperability will improve in the future.

Data Acquisition

Investigations showed that a step-by-step approach to implementing Industry 4.0 in plastics processing is target-oriented. We start with the definition of the use case. Based on this, an initial model for prediction can be developed with a focus on this use case. The validated model can then be integrated into the IT landscape, which is then rolled out in the factory or the entire production network. This is also reflected in the developed model for the implementation of Industry 4.0 in the factory (**Fig. 1**).

Many expert organizations are currently also dealing with this topic and specifically with the standardization of data. For example, there are also recommendations from the VDI group on which signals should be recorded in the field of injection molding [3].

Newer machines offer increasingly better data availability, i.e. they also enable more and more high-frequency recording of the individual signals and their storage as time series curves. This enables in-depth process analyses, which are essential depending on the use case. For the cyclic export of process parameters, the Euromap 63 and Euromap 77 (OPC UA) interfaces also play an important role here.

Implementation of the Smart Factory

At the Institute of Materials Technology and Plastics Processing (IWK), it was possible to set up a data acquisition system to which five different injection molding machines from various manufacturers

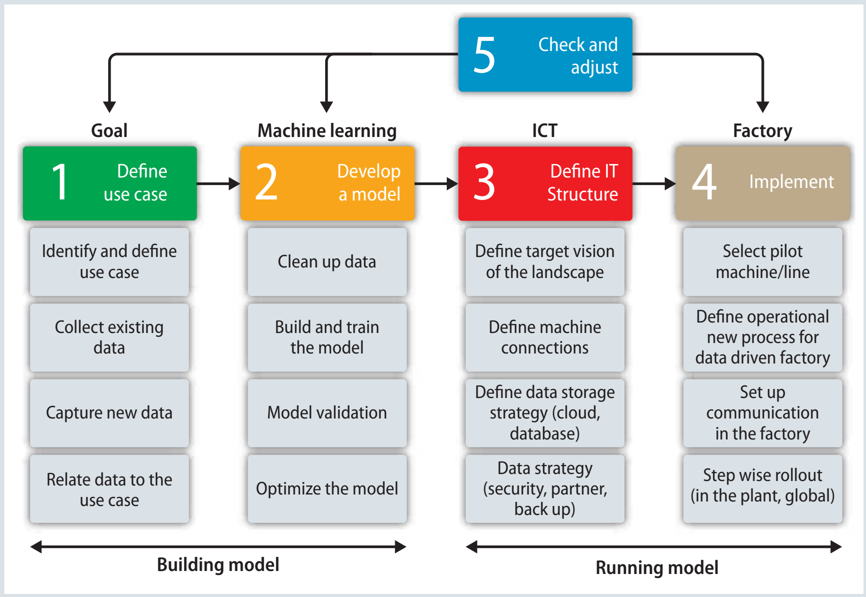

Fig. 1. Model for the implementation of machine learning in the factory Source: © OST – Eastern Switzerland University of Applied Sciences; graphic: © Hanser

and various peripheral devices have now been integrated. The recorded data can be visualized and evaluated directly.

A number of challenges had to be overcome in order to set up this type of data acquisition for machine learning. It became clear that device-specific solutions often had to be implemented so that the data could be exported and recorded in the desired quality. This is a hurdle for smaller manufacturing companies in particular, as such interdisciplinary know-how is often not available.

Another difficulty is the synchronization of data from different machines and devices (e.g. injection molding machine, temperature control units, ambient conditions). Each device usually works with its own time stamp. This is a common problem, especially when working with time series of different devices. This can be avoided by setting up a live system in which all data is recorded synchronously. The time stamp is assigned by the data acquisition system. However, this requires that all machines and devices provide the data live. This means that curve data, which for example is made available via the OPC UA interface at the end of the cycle as time series histories, is not suitable for this purpose. A direct query of strongly time dependent signals (e.g. injection pressure or screw position) via OPC UA in high frequency is not suitable due to the limited publishing interval of the interface (usually max. 200 to »

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The Series Continues

The last article in this series takes a look at the challenges involved in implementing specific use cases and learning from data with the help of artificial intelligence in the field of compounding production technology.

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500 ms). However, it is possible to query pre-calculated parameters (such as maximum or average values) at the end of each cycle, and these data can also be combined with curve data. Nevertheless, aggregation already results in a loss of information. Depending on what is to be learned from the data, this can of course be critical. Older machines, which do not support such interfaces and do not store raw data at all due to limited storage capacities, present an additional difficulty.

In addition to synchronization, the allocation of data from different pre or post-processes is also an issue. On the one hand, data acquisition differs between continuous processes, e.g. material drying, in which continuous time series are recorded, and discontinuous processes such as injection molding and, for example, welding as a follow-up process, in which the data are recorded for each cycle and at a defined sampling rate. On the other hand, the data from the pre-process steps must then also be able to be clearly assigned to the later data of the part. For injection molding, this means which material batch was processed and how long was the material used, to manufacture the molded part, pre-dried? This is not a simple question, which is why it is currently still being worked on. For follow-up processes, this is much easier, since the part and the associated data already exist and only need to be expanded.

Fully Automated and Self-Learning Manufacturing Cell

One implementation of this connected factory is a manufacturing cell for the production of a floorball (**Title figure and Fig. 2**). The ball halves are manufactured on an injection molding machine, laser marked, completely measured in three dimensions and then stored in an interim storage system sorted by color. A collaborative robot is used for automated handling.

For customer orders, this robot takes the ball halves in the desired color from the storage system and transfers them to the welding machine, where the halves are welded into a ball fully automatically. This is a fully connected and automated production cell, the process data of all production steps as well as the quality characteristics are stored in the cloud and can be clearly assigned to each ball. On the one hand, this ensures complete traceability and, on the other, the entire production process can be optimized by using artificial intelligence and advancing towards zero-defect production. This manufacturing cell serves as a training object for students of the OST

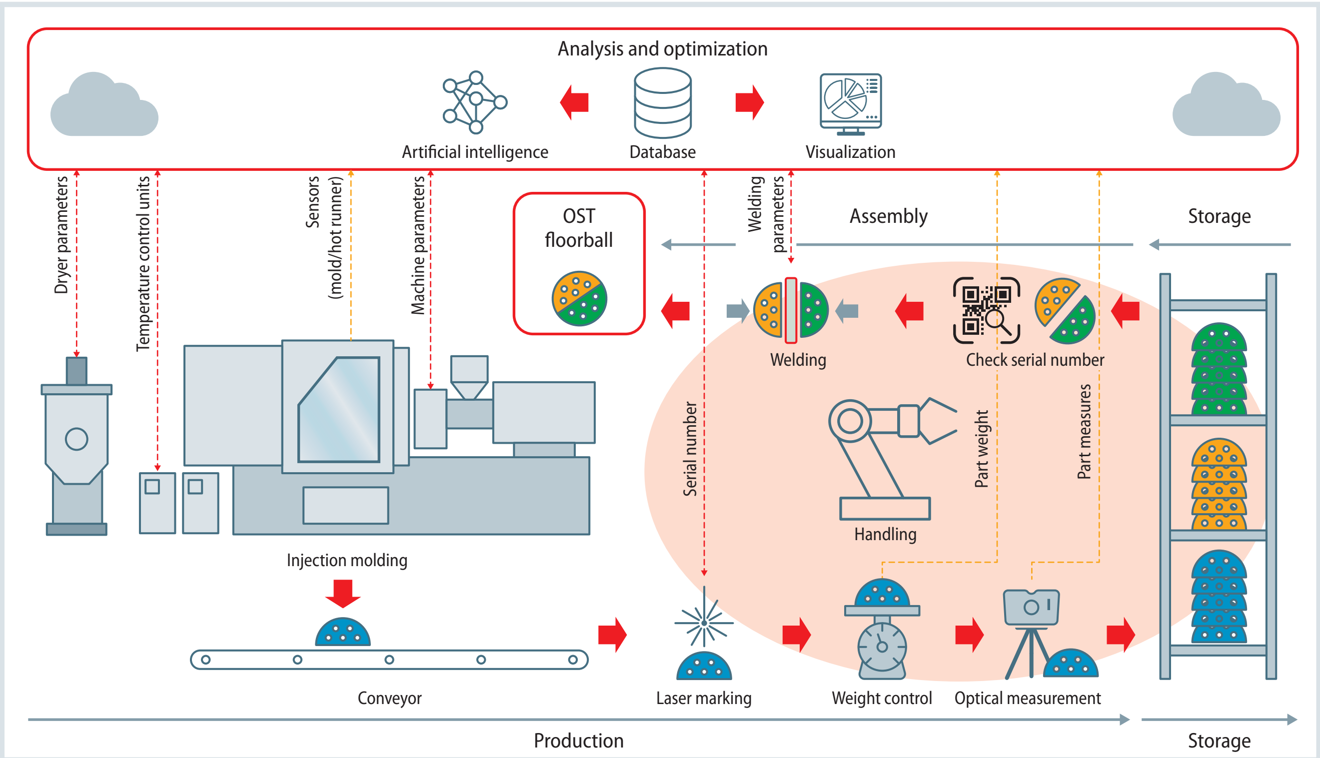

Fig. 2. Production flow of fully automated manufacturing cell Source: © OST – Eastern Switzerland University of Applied Sciences; graphic: © Hanser

–Eastern Switzerland University of Applied Sciences and shows companies the possibilities of digitalization.

Use of Data Acquisition for Research Projects

The data acquisition system also serves as the basis for the use of artificial intelligence in a wide range of projects in the field of injection molding. A central topic is the early detection of process anomalies on the basis of process data. When an anomaly occurs, the machine operator should also be given a recommendation for a suitable countermeasure. This topic is being investigated in a three-year publicly funded research project with five industrial partners.

The process anomalies can be reliably detected and first appropriate countermeasures can be suggested. With the use of a support vector machine and an autoencoder an anomaly score (**Fig. 3, top left**) can be calculated based on various features. This indicates how stable the current process is running. When this score increases, a recommendation for action is suggested to the operator (**Fig. 3, bottom right**), which can be used to correct the process.

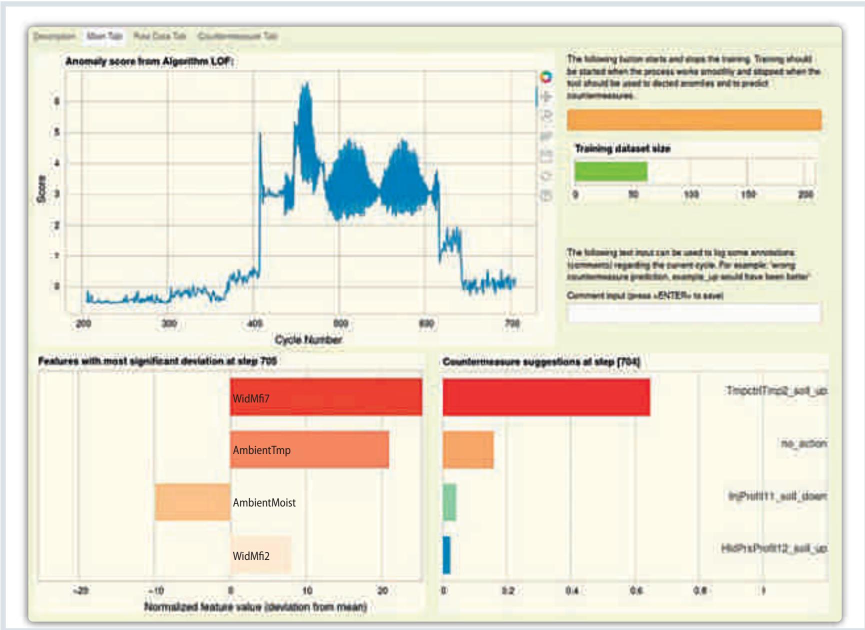

Fig. 3. GUI (Graphical User Interface) for anomaly detection and countermeasure proposal

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Other use cases include the prediction of the quality characteristics of the manufactured parts on the basis of process data and predictive maintenance or detection of wear on tool or machine components. ■