

# Chapter 12

## Approaches of Self-optimising Systems in Manufacturing

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**Abstract** Within the Cluster of Excellence “Integrative Production Technology for High-Wage Countries” one major focus is the research and development of self-optimising systems for manufacturing processes. Self-optimising systems with their ability to analyse data, to model processes and to take decisions offer an approach to master processes without explicit control functions. After a brief introduction, two approaches of self-optimising strategies are presented. The first example demonstrates the autonomous generation of technology models for a milling operation. Process knowledge is a key factor in manufacturing and is also an integral part of the self-optimisation approach. In this context, process knowledge in a machine readable format is required in order to provide the self-optimising manufacturing systems a basis for decision making and optimisation strategies. The second example shows a model based self-optimised injection moulding manufacturing system. To compensate process fluctuations and guarantee a constant part quality the manufactured products, the self-optimising approach uses a model, which describes the pVT-behaviour and controls the injection process by a determination of the process optimised trajectory of temperature and pressure in the mould.

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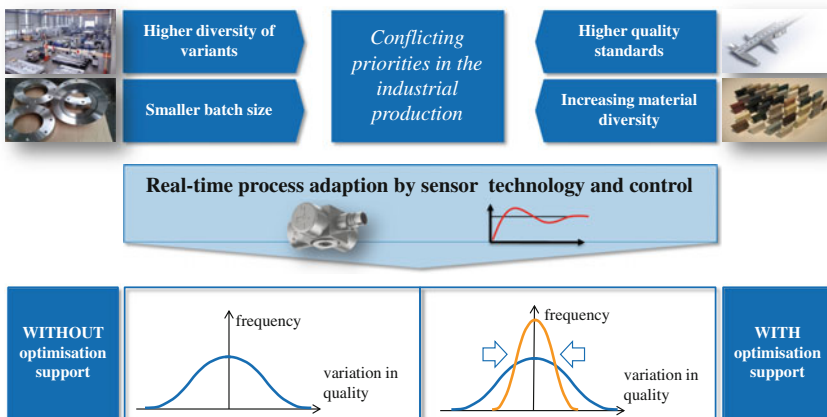
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## 12.1 Self-optimising Systems in Manufacturing

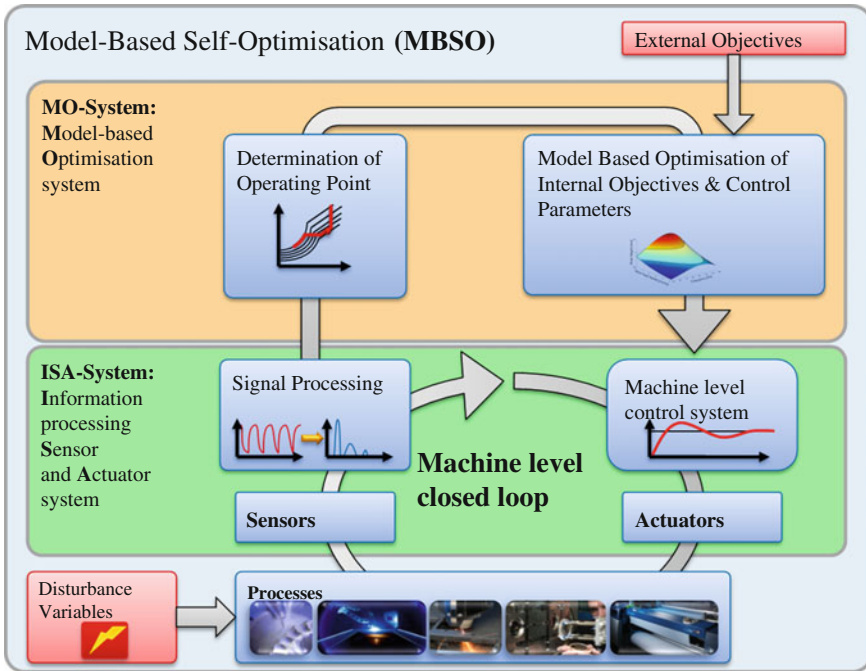
The industrial production is caught between uncertainties and relative lack of precision (upper part of Fig. 12.1). Higher diversity of variants, smaller batch sizes, higher quality standards and increasing material diversities are conflicting priorities in the industrial production that have to be concerned in the future. The lower part of Fig. 12.1 illustrates the vision of process optimisation using sensor and control technologies to reduce variations in quality in contrast to conventional production without optimisation strategies. Self-optimising systems are high level control structures with abilities to analyse data, to model manufacturing processes and to make decisions where deterministic control functions do not exist.

A general overview on self-optimisation including a precise definition is given by Adelt et al. (2009). Approaches to integrate self-optimisation into technical processes and systems are manifold. Klaffert (2007) presents a self-optimising motor spindle that adjust its dynamic properties according to the respective machining situation autonomously. Kahl (2013) transferred the self-optimisation idea to the design process of mechatronic systems in order to improve the manageability of the complete development process.

To achieve the visionary scenario of production, research activities within the Cluster of Excellence focus on the development of self-optimising manufacturing systems. Therefore, a generic framework has been defined in the first development phase, compare Thombansen et al. (2012). In Fig. 12.2 the basic structure of the model-based self-optimisation approach and its modules are shown. The approach is structured in two parts: The “Model-based optimisation system (MO-System)” and the “Information processing Sensor and Actuator system (ISA-System)”.



**Fig. 12.1** Industrial production caught between uncertainties and relative lacks of precision—Klocke (2014)



**Fig. 12.2** The model based self-optimisation system—Thombansen et al. (2012)

The MO-System is the upper layer of the self-optimisation and implies the determination of optimal operating points and the self-optimisation strategies. The input parameters of the MO-system are the production plants external objectives; the output parameters of the MO-system are internal objectives and optimised control parameters for the ISA-system. The ISA-system is a real-time control loop with intelligent data analysis, sensors and actuators. The most challenging tasks for an implementation of the self-optimisation systems are on the one hand the identification of appropriate model-based optimisation strategies and on the other hand the provision of required data from the process provided by the used sensors. Most of the nowadays used sensor systems are not able to fulfil these requirements, as the data they provide are not directly usable as an input parameter for the above described system. Consequently, new sensor and monitoring systems have to be developed for the acquisition of real process data. Further challenges for establishing self-optimisation systems in production focuses also on social-technical aspects. It has to be addressed, how humans are able to interact with the self-optimising systems and how transparency at any state of the process can be ensured. In the following two chapters implementation examples are shown. The first example demonstrates the autonomous generation of technology models and the generation of technology knowledge, which is the core requirement of self-optimising systems. In the second example an established model of the pvT-behaviour in injection moulding is used to calculate the

optimised pV-T-trajectory of the holding-pressure phase. This empowers the system to react to environmental disturbances as temperature fluctuations and ensure constant qualities of the moulded parts.

## 12.2 Autonomous Generation of Technological Models

Self-optimisation requires a resilient knowledge basis in order to realise the objective-oriented evaluation and controlled adaptation of system behaviour. Transferred to manufacturing processes, this knowledge basis should include an appropriate description of the relevant cause-effect relationships as these represent the response behaviour of the manufacturing process. According to Klocke et al. (2012), cause-effect relationships can be modelled in four different ways: physical, physical-empirical, empirical and heuristic. The first two assume that relations can be completely or partly described by natural or physical laws. In case of physical-empirical models missing information is provided by measurements or observations of the analysed manufacturing process. This procedure is applicable if all physical relations are unknown. In this case, the cause-effect relationships can be modelled on the basis of empirical data. In contrast to that, heuristic models are derived from expert knowledge.

Since process models are an important prerequisite for the self-optimisation system, effective procedures for the identification of useable process models have to be developed. In this context, an innovative approach has been developed for the manufacturing process milling within the Cluster of Excellence. This development enables a standard machine tool to determine physical-empirical or empirical models for a given parameter space autonomously. This implemented system is illustrated in Fig. 12.3.

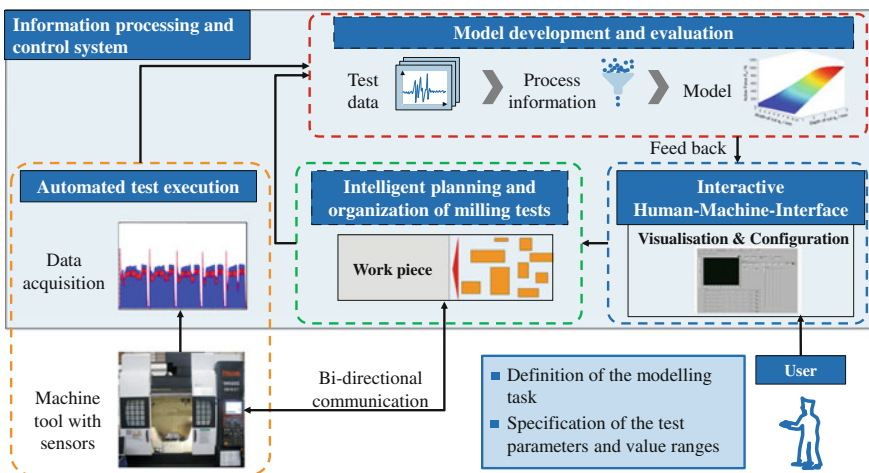


Fig. 12.3 Technology assistance system to generate process knowledge

Figure 12.3 shows the connection of an external information technology system (IT-system) to the machine tool. The IT-system fulfils two main functions. On the one hand, it operates as superior control system in order to realize the aspired system autonomy. On the other hand, the IT-system ensures the communication to the operator. Based on these two main functions, the following system modules have been designed and developed:

- An interactive human machine interface,
- a planning and organization procedure milling tests,
- an automated execution of milling tests and
- the automated modelling and evaluation of the conducted trials.

These system modules are described below.

### ***12.2.1 Interactive Human Machine Interface***

The communication to the operator is an important aspect. On the one hand, the autonomous system requires information of the used machine tool, the work piece, the cutting tool and the modelling task for its own configuration and documentation. Meta information on the test conditions are directly linked to the test results in order to enable a reuse of the obtained data and information. On the other hand, relevant system actions and the obtained test results need to be reported to the operator. Thus, a sufficient system transparency can be ensured, which ensures the acceptance of the autonomous system by the operator.

An interactive configuration wizard is developed for the first communication part. Interactive means in this context, that the input is checked for plausibility and the operator is alerted in case of incorrect entries. The technological limits of the machine tool and cutting tool are compared to the value ranges of the investigated parameters. Thus, it is not possible to define for example a cutting speed that will exceed the maximum spindle speed. Another example for the plausibility check is the comparison of entry data with technologically sensible limits. This supports the documentation process by identifying possible input errors such as a helix angle larger than 90°.

The second communication part is realised via a display window on an installed screen at the machine tool. This display is updated continuously while the autonomous system is running. It shows the planned test program, current actions like data transmission, test execution or model coefficient determination, as well as status messages such as “monitoring is active” or “disturbances occur”. The illustrated information assists the operator to understand the behaviour and the decisions of the autonomous system.

### 12.2.2 Planning and Organisation of Milling Tests

As a first step, the planning and organisation module is responsible for the automated definition of test points. Test points are a suitable combination of feeds and speeds for a given test material. For this purpose, design-of-experiments methods are integrated into the autonomous system. Based on these methods the system determines appropriate parameter constellations which are investigated in milling tests.

When all test points are defined, the milling tests need to be distributed over the given work piece. This organisational step is required in order to define the starting positions of the tool during the automated testing phase. Figure 12.4 shows the approach to solve this distribution task.

Each milling test can be described as a rectangle with a certain width and height corresponding to the geometrical dimensions of the cut. Similarly, the lateral area of the work piece can be described by rectangular shapes. Based on this the so-called bin packing algorithms can be used to distribute the rectangles over a work piece, Dyckhoff (1990). On the upper right side of Fig. 12.4 an exemplary distribution result is illustrated. It shows a bin packing algorithm applied to rectangles which are pre-sorted according to their heights. Each of the rectangles and therewith the position of each milling test is thus clearly defined.

Before the planning and organisation phase can be completed the distribution result must be transferred to a machinable sequence of cuts which can be performed automatically. This includes not only the milling tests but also cuts which are needed to remove material and to clean the work piece. Cleaning cuts are necessary in order to avoid collision and to ensure accessibility to the next test cut. The determination of the whole cutting sequence is achieved by digitising the rectangles

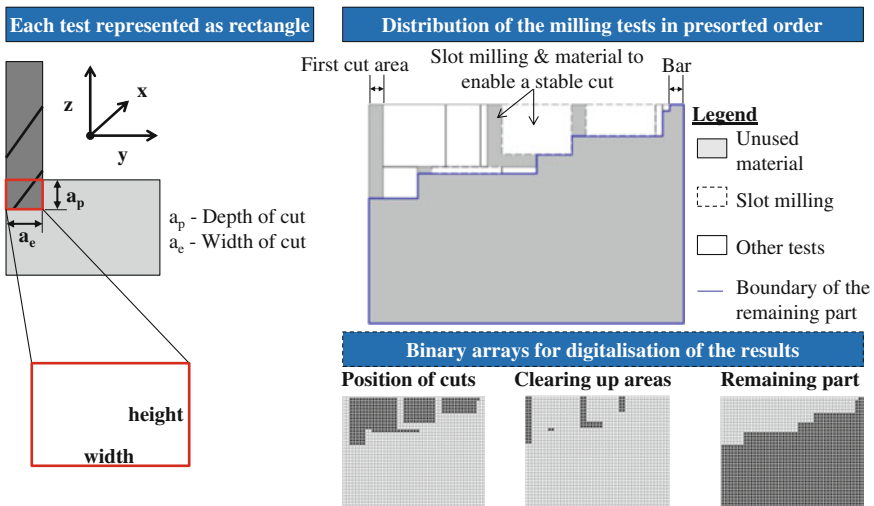


Fig. 12.4 Rectangle distribution

distribution. For that purpose, binary matrices with a defined grid size are used. The result of this process is also presented in Fig. 12.4.

### ***12.2.3 Automated Execution of Milling Tests***

The automation sequence uses a conventional line milling strategy for the execution of the milling trials. Because of this simple process kinematic the milling tests can be easily standardised and adapted to different cutting conditions. Furthermore, the starting and endpoint are clearly defined. This leads to a tool path, which can be easily implemented in a parameterised NC program.

Based on the standardised test procedure an automation sequence has been developed, which contains all steps such as the execution of milling operations, data acquisition as well as data analysis and processing. After each milling test the process relevant characteristic values are available and stored in a data base.

A further step focused on the implementation of an appropriate communication interface between the machine tool and the external IT-system. Via the communication interface several actions are realised. These are:

- **Triggering:** For a controlled process it is necessary to synchronise actions between machine tool and external IT-system. Trigger functions are used to announce that a sub system is ready.
- **Data transmission:** Values for process relevant parameter such as spindle speeds, feed velocities and tool centre point position need to be transferred from the external IT-system to the machine control. Therefore, a 16-bit data transmission has been installed.
- **Error messaging:** In the event of errors, the sub system needs to inform all involved systems. This can be another subsystem or the machine tool controller itself. For this purpose, programmable logic controller (PLC) variables of the machine tool are used. Each error type is assigned to another PLC variable.

### ***12.2.4 Modelling and Evaluation***

After the execution of all machining trials, the autonomous system determines the empirical model coefficients for an arbitrary number of predefined model functions. For this purpose, a generic optimisation algorithm is integrated. Based on the coefficient of determination  $R^2$  as target function, the generic algorithm evaluates iteratively various constellations of model coefficients until the desired model accuracy is achieved. According to Auerbach et al. (2011) the coefficient of determination is a suitable error measure to compare different models with each other. After the determination of the optimised coefficients by a genetic algorithm,

the best model is selected by the autonomous system. This is presented to the operator via the visualisation interface.

For the identification of possible model functions, a black-box modelling approach with a symbolic regression has been applied. Symbolic regression allows the approximation of a given data set with the help of mathematical expressions. Thus, it is possible to identify surrogate functions which represent the cause-effect relationships of the investigated machining process. The suitability of the model function with regard to the technological correctness and its complexity has to be evaluated by the technology expert.

### 12.3 Self-optimised Injection Moulding

In injection moulding the transfer characteristics of the conventional machine control to the process variables can vary by external influences and changed boundary conditions (Fig. 12.5). The conventional injection moulding machine control bases on machine variables. Thus, identical courses of machine variables lead to different process variables in different production cycles. These additional disturbances result in a fluctuating part quality. To increase the process reproducibility the concept of self-optimising injection moulding should compensate occurring process variations.

Fluctuating ambient temperature or varying material properties are systematic disturbances and can affect the product quality heavily. This includes the changes in the heat balance of the injection mould. Fluctuations in the heat balance of the mould occur for example by a non-identical repetitive process such as after changing machine parameters. Therefore, an autonomous parameter adaption has to compensate fluctuations, i.e. in the heat balance of the mould. In contrast to the machine variables process variables provide detailed information about the processes during the injection and holding pressure phase. The cavity pressure path over time for

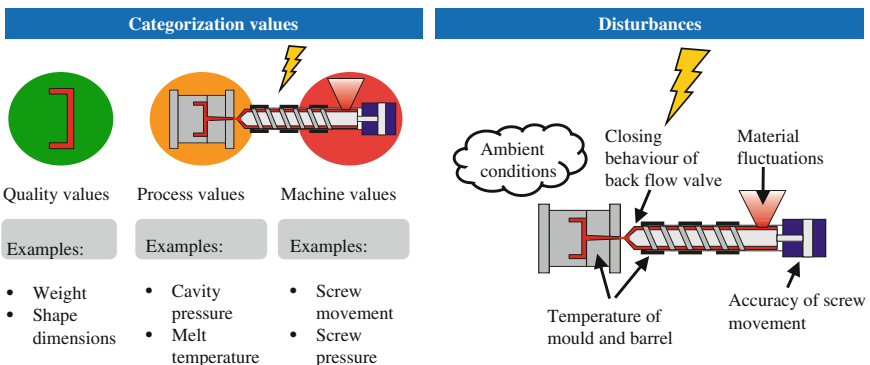
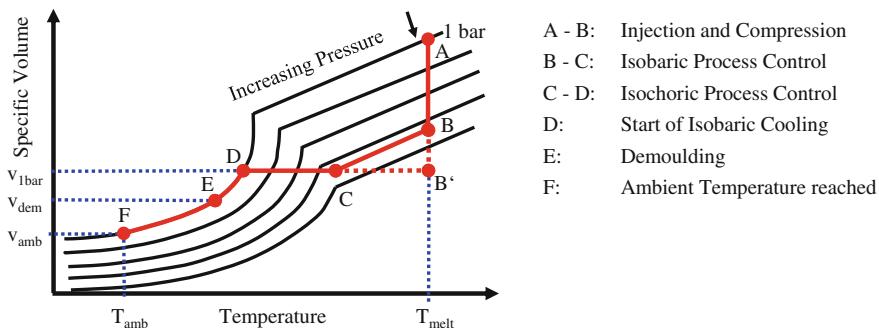


Fig. 12.5 Variables in injection moulding and typical disturbances





**Fig. 12.6** pvT-Diagram as suitable model for the optimisation of holding-pressure phase

example correlates with various quality variables such as the part weight, the part precision, the warpage and the shrinkage, the morphology and sink marks.

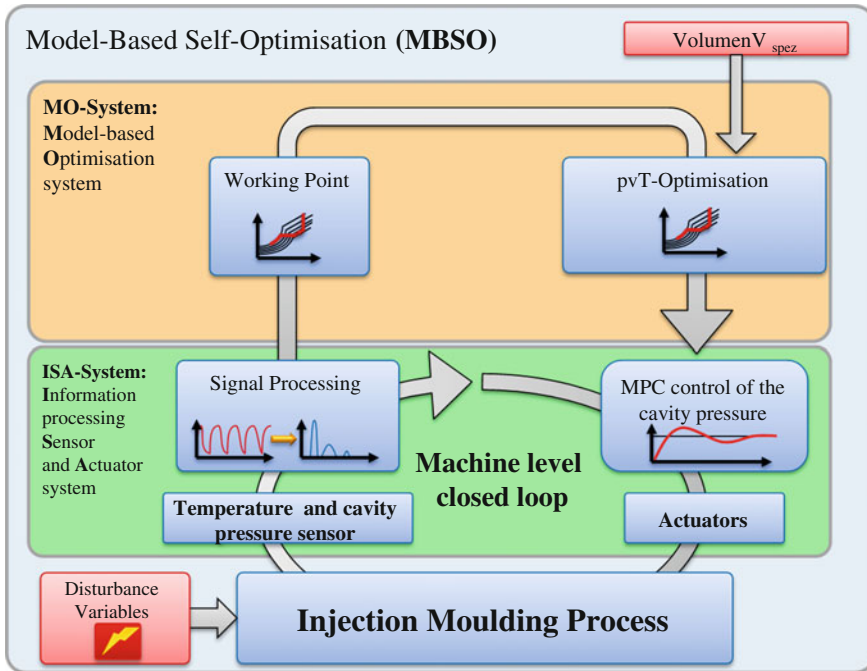
Due to the presence of disturbances acting on the injection moulding process, an exclusive control of machine variables does not guarantee an ideal reproducibility of the process and thus constant part properties. Using the pvT-behaviour as a model to map process variables to quality variables, the course of cavity pressure can be adjusted to the actual path of melt temperature. Based on this context, the concept for the self-optimising injection moulding process is derived.

The pvT-behaviour represents the material based interactions between pressure and temperature in the mould of a plastic. It depicts the relationship between pressure, temperature and specific volume and thus allows a description of the link between the curves of cavity pressure, melt temperature and the resulting part properties in injection moulding.

The aim of the self-optimising injection moulding process is to ensure a constant quality of the moulded parts by realising an identical process course in the pvT-diagram (Fig. 12.6). The first requirement is to always achieve an identical, specified specific volume when reaching the 1-bar line (D) in every production cycle. This ensures a constant shrinkage in every cycle. Based on this requirement, the second requirement is to achieve an isochoric process course (C–D), which is characterised by the constant realisation of the given specific volume during the entire pressure phase. Due to the limits of machine the isobaric process control (B–C) is preceded the isochoric process control. Before, the injection and compression phase (A–B) is conventionally controlled by machine values.

At the Institute of Plastics Processing (IKV) a concept for a self-optimising injection moulding machine is being developed. The concept of self-optimising at injection moulding is divided in the MO-System using a model, which is based on the material behaviour, and ISA-Systems, which includes the determination of the melt temperature and a cavity pressure controller (Fig. 12.7).

Based on the conventional injection moulding process the cavity pressure is measured by piezoelectric pressure sensors. The melt temperature is approximated based on the melt temperature in the screw and the mould temperature using the

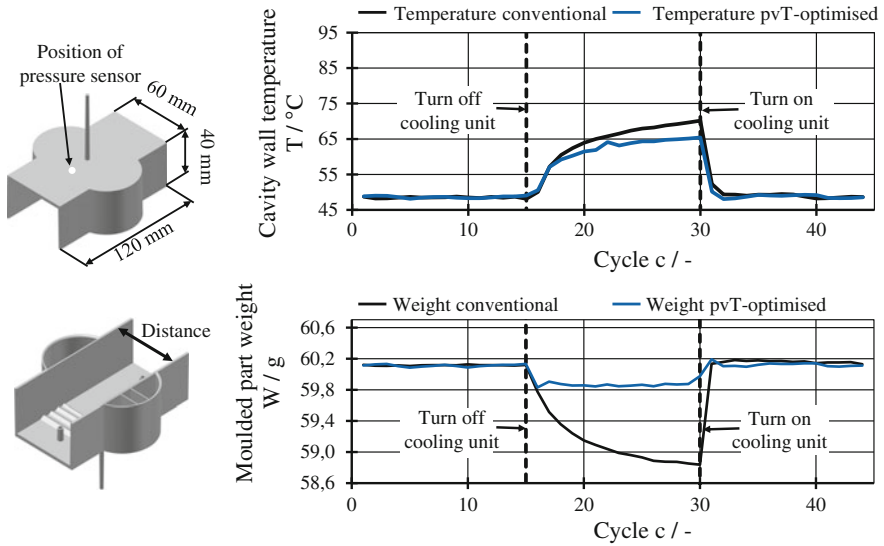


**Fig. 12.7** Transfer of the self-optimising concept to the injection moulding process

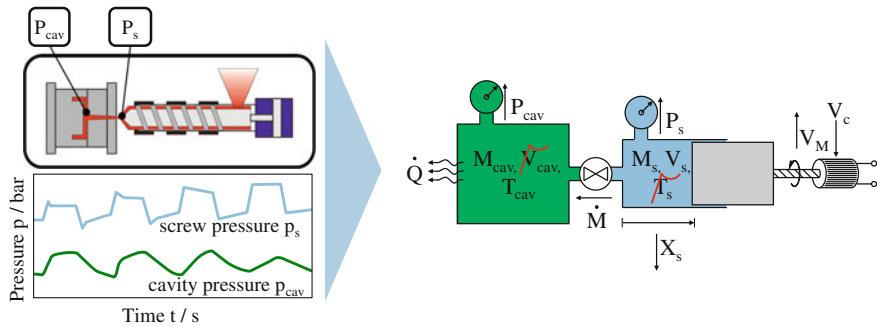
cooling calculation or directly measured by IR-Sensors (Menges et al. 1980). After determination of the temperature and pressure in the cavity the working point and the optimised trajectory of the pressure can be calculated based on the material specific pvT-behaviour. A Model Predictive Controller (MPC) realises the pressure trajectory autonomously. Using the cavity pressure controller allows to compensate the pressure variations in the cavity. This reduces the natural process variations. Furthermore, the adjustment of the cavity pressure trajectory to the measured temperature in the mould results in the compensation of temperature fluctuations.

To simulate temperature fluctuations the cooling units of the mould are turned off in an experiment after 15 cycles. The temperature path in the mould and the weight of the moulded part is observed using the conventional injection moulding process and the self-optimised concept (Fig. 12.8). Compared to the conventional processing the weight reduction can massively be reduced by using the self-optimised processing concept.

To realise a pvT-optimised injection moulding process the user-friendly implementation of a cavity pressure control is fundamental. The cooperation of the Institute of Plastics Processing (IKV) and the Institute of Automatic Control (IRT) focuses on the autonomous adaption of the cavity pressure control on boundary conditions to simplify the configuration of the cavity pressure controller. Therefore, a dynamic model for a MPC is developed for the injection moulding process (Fig. 12.9).



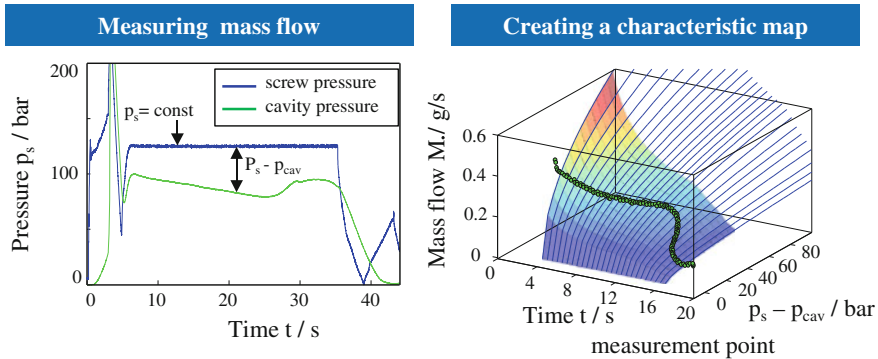
**Fig. 12.8** Compensating temperature fluctuations with self-optimising concept compared to conventional processing in injection moulding



**Fig. 12.9** Dynamic model of the MPC to control the cavity pressure

The model describes the correlation of the pressure in the screw ( $P_s$ ) and the cavity pressure ( $P_{cav}$ ). Therefore, the system is modelled with two vessels and a valve (Hopmann et al. 2013). To adapt the physical motivated model to the time invariant measurements a time variant parameterisation of the valve is used.

The model is parameterised during an identification cycle. Therefore, a production cycle with a constant screw pressure is realised (Fig. 12.10). Conventionally the screw pressure is controlled in injection moulding. In the current configuration a simple PID-controller is used to realise the constant screw pressure. The difference of the screw pressure to the cavity pressure is measured to detect the mass flow between the vessels over the time. Based on the acquired data a characteristic map is created.



**Fig. 12.10** Identification of time variant mass flow in the valve

Beforehand, the acquired data cannot be calculated and thus an easy parameterisation is necessary. The advantages of identification process are varied. A constant screw pressure is feasible and can be incorporated into real-life workflow. The current concept of the self-optimisation injection moulding should be extended by cross-cycle optimisations to counteract disturbances such as viscosity fluctuations. The combination of online control and cross-cycle optimisation is necessary to compensate the heat household fluctuations after changing machine parameters. The compensation of the thermal fluctuations can be accomplished by the use of the previous concept of self-optimising injection moulding machine.

## 12.4 Summary and Outlook

The examples of implementation demonstrate the step wise development towards the vision of self-optimised manufacturing systems. The autonomous generation of technology models highlights the machine-human interaction approach of automated modelling as the human has a leading and control function in the context of the optimisation system. As by today automated systems are not able to capture all boundary conditions, exceptions and environmental impacts, the machine operator determines the limits and interacts in non-deterministic situations as a decision maker and handles exceptional situations. The automated modelling system enables the development of models by providing an integrated environment for experimental planning by design-of-experiments, deterministic processing of experiments and establishment of machine readable models.

The example of self-optimised injection moulding applies the already known pvT-model for the optimisation of quality features as the specific volume of the moulded parts. The implementation of the model towards a self-optimised production system describes the step-wise procedure to reach optimisation by physically describing the process behaviour and subsequent empirical parameter

identification. The result of the optimisation process is a robust process being automatically adapted to temperature fluctuation in the environment. Based on the described work an automated identification process should be possible and further research is conducted on this.

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