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Self-optimizing production systems

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Abstract

Today's manufacturers are facing numerous challenges such as highly entangled and interconnected supply chains, shortening product lifecycles and growing product complexity. They thus feel the need to adjust and adapt faster on all levels of value creation. Self-optimization as a basic principle appears a promising approach to handle complexity and unforeseen disturbances within supply chains, machines and processes. Therefore it will improve the resilience and competitiveness of manufacturing companies.

This paper gives an introduction to the concept of self-optimizing production systems. After a short historical review, the different levels of value creation from supply chain design and management to manufacturing and assembly are analyzed considering their specific demands and needs for self-optimization. Examples from each of these levels are used to illustrate the concept of self-optimization as well as to outline its potential for flexibility and productivity. This paper closes with an outlook on the current scientific work and promising new fields of action.

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Keywords: Artificial intelligence; Optimization; Control; Management

1. Introduction

Manufacturing companies are facing a large number of challenges on different levels. On management level, changing customer demands, a dynamic environment and quality problems are requiring companies to adapt themselves and their processes faster to new boundary conditions leading to reschedules in supply as well as to turbulences in value chain and supplier networks. On the level of manufacturing and assembly processes, a faster adaption and reconfiguration is required by customer-specific demands and small lot sizes.

Thus, two aspects are critical for shorter innovation cycles and high productivity. First, an integrated knowledge of materials, resources and processes helps to predict the system behavior and optimize the production process. Second, adaptability and viability are crucial for success under unpredictable and volatile boundary conditions. The first aspect comprises deterministic models that reduce complexity to a mathematical or logical form that describes the essential interactions within the system. A simple example is the reduction of machine dynamics to a multi-mass-system for designing the mechanical structure. Integrating multiple physical or socio-technical domains, however, it becomes

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increasingly difficult or impossible to make accurate predictions with first-principles. Instead, adaptability and viability of the system are of increasing importance to achieve the targeted system state. This requires cybernetic models that can handle complexity rather than reducing it. Here, effective control structures are more significant than accurate predictions.

Self-optimization aims to combine the advantages of cybernetic and deterministic models to design systems that are able to change their internal state or structure endogenously according to changes of the external conditions [1]. This means that a deterministic model is put into a cybernetic structure. On the one hand, feedback from the production system is used to determine the system state. On the other hand, the model itself can be continuously improved in prediction accuracy by comparing sensor data with calculations. The deterministic model therefore is the basis for changing control structures and target systems.

The concept of self-optimization is thus regarded as a promising approach to overcome the challenges mentioned above. Therefore, this article gives an introduction of the general concept of self-optimization for production systems and its specific characteristics and adaptions on the different levels of value creation.

2. Historical Background

While first ideas of cybernetics date back to the water level controller of Ktesibios (~250 BC), the theoretical basis has been developed only about 70 years ago by WIENER [2]. Self-optimization is usually seen as a subdomain of cybernetics and builds on the idea of resembling different divisions of biological nervous systems up to "intelligence" with nested and cascaded control loops or higher-order and structural adaptions. A famous early representative of this approach is ASHBY with his concepts of "ultra-stability" and "homeostatic devices". The main idea behind these concepts is the ability of a system to adapt to changing environments by reinforcement and learning leading to a choice of parameters that avoid a critical status [3].

Only few years later, KALMAN was the first to speak of self-optimization for control systems. In his description, such a system is able to conduct a three-step-logic to ensure stability and continuously optimize itself:

(1) Determination of the process' dynamic properties
(2) Conclusion of the requirements and characteristics for a control system
(3) Implementation of a control system with standard elements.

These steps are executed continuously and automatically [4]. While the theory of linear systems as introduced by WIENER has been widely explored during the last decades, modern control theory often deals with non-linear systems and derives control parameters from the optimization of an objective function under constraints. SKOGESTAD refers to this idea, but argues that for many systems near-to-optimal control can be achieved by keeping adequate controlled variables at setpoints, thus avoiding solving the objective function explicitly [5]. SKOGESTAD illustrates his idea with the problem of long-distance running. Here, rather than keeping the running speed constant, a constant heart rate is likely to assure a "stable" run also in hilly terrain. All other variables of the physiological system "optimize themselves" by keeping the heart rate constant. Therefore, a control unit is introduced to stabilize the process at a aspired operating point or level [6]. If disturbances occur or another operating point appears more desirable, a super-imposed optimization system changes the control parameters in non-real time applications.

During the last decade the idea of self-optimization has been applied to a wide range of technical systems. For example the idea of self-optimization has been applied to the development of mechatronic products in the course of the Collaborative Research Centre "Self-Optimizing Concepts and Structures in Mechanical Engineering". A three-step-logic is used here, reflecting KALMANs basic concept of controller adaption due to changing process and environmental conditions. Here, self-optimization relies heavily on a so-called "Operator-Controller Module" featuring three different layers such as real-time controllers, a cognitive optimization unit and an intermediary reflectory layer for quick controller adaptions [7].

During the last years the concept of self-optimization has been applied to the specific requirements and conditions of production systems in the Cluster of Excellence "Integrative Production Technology for High-Wage Countries" at RWTH Aachen University.

3. Framework for Self-Optimizing Production Systems

Interconnected production facilities can be regarded as complex, socio-technical systems. These socio-technical systems involve the mutual inter-relationship between humans and technical systems considering the human operator as an integral part. But in the historical context the concept of self-optimization is mainly used for technical systems.

According to the levels of automation [8], self-optimization can occur on different levels, for example as a system that supports the human operator via giving him different options for his action in the area of production planning or as an almost autonomously working system when considering manufacturing processes. However, the operator must have the necessary knowledge concerning the system state independent of the degree of automation at all times. Especially as self-optimizing systems have a high degree of autonomy, the human operator is confronted with many unexpected behavior patterns.

Table 1. Examples of levels of automation due to Sheridan.

Level	Degree of automation
1	Computer offers no assistance, human must do it all.
4	… suggests one set of action
10	… decides everything and acts autonomously, ignoring the human

Therefore, a sub-project of the Cluster of Excellence examines human-machine interaction in self-optimizing production systems. The long-term objective is that the human and the cognitively automated system can operate safely and reliably in terms of a socio-technical system. In order to achieve this, the behavior of the technical system has to be transparent to the human and it has to be perceived and accepted as a co-worker.

In 2014, SCHLICK et al presented the self-similar structure of self-optimization for production systems, which serves as a general framework in this context [9], as depicted in Fig 1. The following description of Fig. 1 is an excerpt from [9].

The bottom level of the architecture represents the numeric (sub-symbolic) information processing of the automatic control systems. In the next higher levels, the adaptation process is based on “cognitive controllers” on a more abstract level (symbolic). Their decision-making process is based on the current system state in conjunction with the pursued goal. In particular, they generate or update a model of the controlled process in conjunction with the environment within the model builder. This model contains the execution conditions of the production process as well as the information of the interacting subsystems in the appropriate granularity. Based on the model, the optimizer and decision unit are able to make context-sensitive decisions. At the machine level, for instance, functionalities of a model-based self-optimization [10] are realized whereas the cell level aggregates several machines to higher level production units following coordinated actions. Finally, the segment can be considered as a macro structure combining several cells for the overall production process. The level of abstraction correspondingly increases from process level to segment level. The type of information that is processed also changes. The automatic control is based on continuous spatiotemporal signals whereas the controllers at machine, cell and segment levels use a symbolic representation of the state information. At each of the higher levels, a human operator interacts with the cognitive controller [11]. This can be a physical interaction, such as at machine level, but are more usually

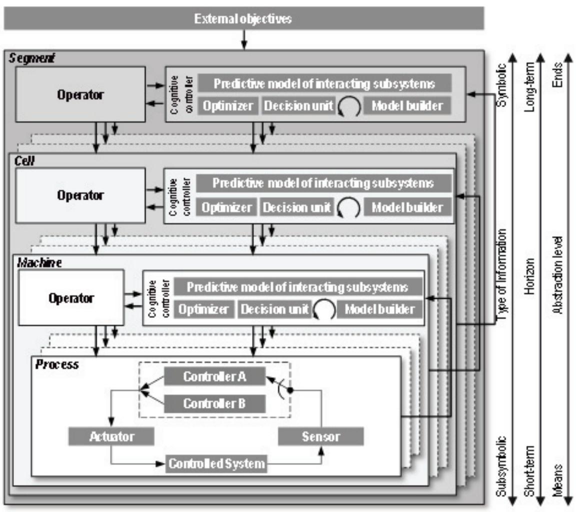

Fig. 1. Self-similar structure of self-optimization for production systems (adapted from [11])

supervisory control tasks processed in order to monitor the system behavior. The system therefore requires ergonomic human-machine interfaces to display information, enable the operator to recognize the current state of the system, to understand its functional state and behavior, and to be able to intervene if necessary.

The optimization criteria of the production system are determined by both external and internal objectives. External objectives, such as constraints regarding the lead time or costs, are processed at each level and propagated to the next lower system. Each subsystem on the individual levels generates additionally its own internal objectives. At the machine level, this could be constraints regarding wear and tear or energy consumption whereas at higher levels the objectives could relate to, for instance, throughput and utilization. On account of the self-optimizing functions, the systems are able to adjust their internal objectives to adapt to environmental changes in the production process [10]. As long as the internal objectives do not contradict the external objectives or objectives generated by higher order systems, they can be adjusted and altered by the corresponding cognitive controllers. In this way, systems can generate additional constraints for their subordinated systems.

The self-similar structure serves as a general framework for the application of self-optimization in production systems. Still, adaptions need to be made to meet the necessities and requirements of specific areas within industrial production. Thus, the challenges and context specific adaptions of self-optimization for production management, manufacturing and assembly systems will be detailed in the following chapter.

3.1. Production Management

While a lot of applications of self-optimization are aiming at technical processes, the management level is often neglected, leading to the optimization of partial problems but not of the system as a whole. Thus a holistic approach is required which integrates also the management level. This implies the integration of self-optimizing control loops on cell level with those addressing the production planning and control (PPC) as well as supply chain and quality management aspects.

In contrast to the latter, the occurring challenges differ significantly.

3.1.1. Challenge

On a management level, companies are facing a wide range of challenges in the field of customer demand, dynamic environment conditions and quality problems [12]. Companies have to adapt themselves and their processes to dynamic environment conditions like movements in customer demand, reschedules in supply as well as turbulences in networks [13]. Nevertheless, a successful production management is characterized by high process efficiency and a high availability of information. The challenge is to manage negative consequences, such as wrong decisions in the planning processes, caused by poor communication and conventional solution approaches based on centralized planning methods [14]. This leads to a slower and more inflexible reaction of companies on internal and external disturbances and thus to an increasing gap between reality and intention [15].

3.1.2. Context Specific Application

The scope of production management ranges from the level of cross-company cooperation to the level of machine control. Self-optimization for production management systems can be defined as the adaption to an optimal working point due to changing internal and external influences taking into account human-decision behavior. Self-optimizing systems support the human operator by detecting and analyzing the current system status on the different levels of the production management system (e.g. supply chain, company, shop-floor, manufacturing cell and machine) and providing the operator appropriate assistance to continuously improve the operating point.

To cope with the dynamic environment, a cybernetic production management reference model has been developed which integrates the different level of production and production management (see figure 2) [16]. To incorporate human decision behavior, technical and socio-technical control loops are combined. Based on the Viable System Model of Stafford Beer, it defines the necessary planning and control tasks as well as the required and sufficient information channels for a self-optimizing production management. The Viable System Model provides an adequate structure for consistent integration of trans-disciplinary control loops and their alignment to a super-ordinate target system. It serves as a regulatory framework to allocate the planning and decision models within the overall production management context and to derive design requirements [17, 18, 1].

3.2. Manufacturing systems

Manufacturing systems in the current scope are systems that perform one step in the production chain with one specific process. Examples are milling of metals, weaving of fabrics, welding of plates, injection molding of plastic parts or cutting of metal sheets by laser radiation. They all have in common that they process material in order to give it new functionality. Productivity and reliability of such manufacturing systems increase with each generation of machines and their control technology. Suppliers focus on more robust components and integrate faster actuators where possible. New sensors and faster bus systems are applied to enhance control of subsystems and to enable faster synchronized action of all components in the machine. On this path, new manufacturing systems follow given setting parameters better. The next step is the acquisition of knowledge about the process and the system condition to enable the integration into a larger scope as shown in Fig. 1.

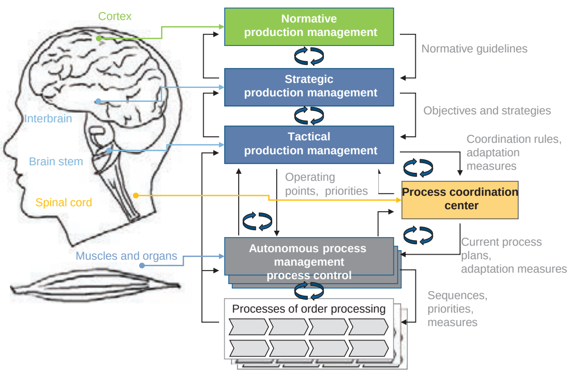

Fig. 2. Concept of the Viable Systems Model

3.2.1. Challenge

Sustainable market success of products require enhanced quality levels. The impact of missing such quality levels can lead to interrupts in the production flow or products that do not meet the requirement of the customer.

Quality is defined differently for each product. Weight of fabrics or surface roughness in laser cutting are only some properties of the manufactured part that determine quality. Looking at the overall manufacturing process, this definition of quality can be extended to include production factors such as use of raw material, time for manufacture or personnel required to finish the part.

Manufacturing systems that are expected to optimize such sets of production factors face the challenge to know a lot about the manufacturing process. Where current systems are optimized towards a precise execution of setting parameters, self-optimizing systems need to optimize towards product quality. This can only be realised if expert knowledge about the process and the boundary conditions is embedded.

3.2.2. Context specific application

Self-optimization for manufacturing systems in the current context can be defined as:

“Self-optimization of a technical system consists of adjusting to changed input values or environmental conditions, without external intervention, based on embedded expert knowledge and direct process information, so that the required output values are achieved optimally” [19].

This definition leads to the approach of Model-based self-optimization (MBSO) [20]. The optimization is based on embedding surrogate models of the process into the manufacturing system. Such models can be created by meta modeling techniques which combine expert knowledge, experimental data and simulation results ([21], [22]). The numerical evaluation enables the translation of external objectives such as product quality, available manufacturing time and resource consumption into internal objectives and control parameters for the manufacturing task. It also enables the interpretation of sensor signals to identify the current operating point of the manufacturing process which leads to an automated prediction of process results [23].

The Model-based Optimization System (MO-System) compares the predicted to the targeted process result which eventually leads to an optimized set of internal objectives.

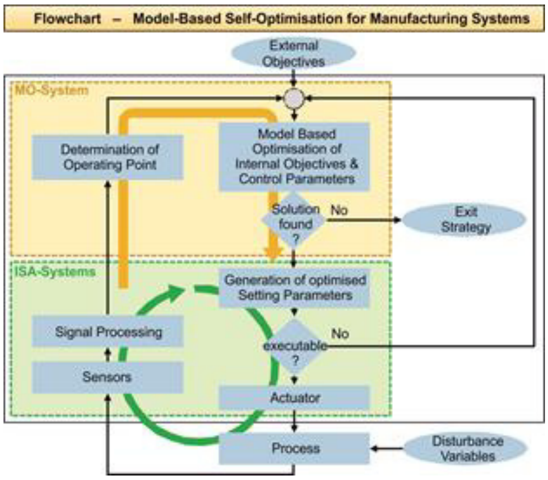

Fig. 3. Model-Based self-optimization for manufacturing processes

These internal objectives are translated into setting parameters by the information processing sensor actuator systems (ISA systems) which control the actuators like motors for the feed rate at the required control cycle times.

The result of a model based optimization facilitated by the separation of time scales is a process that is not driven by a fixed set of input parameters, but one that is optimized towards a set of external objectives such as product quality, manufacturing speed and resource consumption.

3.3. Assembly Systems

Regarding assembly systems the potentials of self-optimization can be leveraged in the field of extreme dimensions because in these regions the influences of uncertainties and environmental disturbances become critical. On the one hand, the conducted work considers large components such as airplane structure elements and on the other hand very small parts such as micro-optical elements used for laser beam shaping. Both areas of application require flexible and responsive assembly solutions due to moderate production volumes in combination with versatile product portfolios. Flexibility is required for covering different products and variants in production scenarios with a high degree of customization. Responsiveness stands for the capability of fast reaction to unpredictable market changes as well as for the capability to efficiently launch new products with a short lead time. This property is required in many branches in order to stay competitive in the future [24].

3.3.1. Challenges

One main task of assembly is to ensure the product function even under the presence of uncertainties. Assembly processes are affected by tolerances and process deviations caused by environmental influences such as gravity, part tolerances or limited actuator accuracy. This requires the use of external sensors as well as robust strategies for interpreting the acquired sensor data. To achieve flexible and responsive assembly solutions and hence to master the challenges of planning, commissioning and executing sensor-based assembly processes, the system for controlling and improvement of the production needs to have the functionality to set and adapt its parameters and the inner system goals (setpoints) for assembly autonomously.

3.3.2. Context specific application

As described in section 1, self-optimization is an approach to handle rising complexity induced through uncertainties. Self-optimizing assembly systems are characterized by their goal-orientation and their capability to overcome the disturbing influences of uncertainties. The work presented in this paper proposes a model-based approach depending on the acquired data for an automated component positioning. With this approach it is possible to achieve functional assemblies under the presence of uncertainties (Figure 4).

The control process of a self-optimizing assembly system is based on three main steps. First, the current assembly state during production is identified by utilizing process integrated metrology for data acquisition. Second, the acquired data is interpreted based on product and machine models. The extracted information describes deviations from the product function. The goal of the analysis is the identification of new setpoints for the assembly system in order to achieve the aspired product function. The third and final step is the adaption of the assembly system in order to reach those setpoints.

Model-based interpretation of the acquired data and the determination of new setpoints are the main concepts of self-optimizing assembly systems. The decomposition of objectives for assembly tasks is a classical approach to reduce complexity and may still be applied for the derivation of cause-effect relationships from product models as discussed in [25]. In the domains of very large and very small part assemblies, this approach leads to suboptimal results because it is either not possible to define independent objectives or the presence of uncertainties leads to conflicting objectives. Therefore, model-based system control in general needs to find a compromise between multiple – possibly conflicting – objectives in order to achieve an optimal system state in the sense of an optimized product function. Self-optimization is an approach to solve this multi-criteria optimization problem.

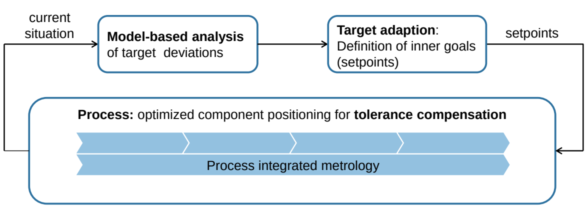

Fig. 4. Control of a self-optimizing assembly system

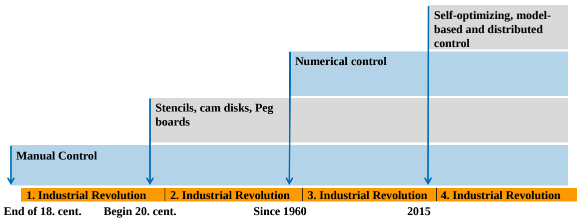

Fig. 5. Self-optimizing control as the basis for the next industrial revolution

4. Summary

In a modern day environment, production systems are facing numerous challenges. In this paper, the concept of self-optimization as used in the Cluster of Excellence “Integrative Production Technology in High-Wage Countries” has been introduced as one way of handling these challenges. While a generalized concept can be used to describe self-optimization in the context of production systems, adaptions and refinements need to be applied to meet the diverging demands of production management, manufacturing and industrial assembly.

In the context of this paper, the general concept of self-optimization for production systems has been discussed regarding its self-similar structure and the integration of the human into a socio-technical system. In addition to that, the diverging challenges and thus necessary adaptions and detail designs on the level of production management, manufacturing and assembly processes have been presented.

Regarding the historical development of control in production engineering, each new control technology was accompanied by a rapid growth of productivity often labeled as “Industrial Revolution”, see Fig. 5. Self-optimization can be regarded as the next step in control technology. Considering developments such as the “Internet of Things” it becomes increasingly important to adjust to new environmental conditions since the environment changes continuously. Moreover, the cooperation of humans and technical systems requires a steady adaption of control structures. Therefore self-optimization is seen as a key-enabler for the next level of productivity increase.

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