Self-optimizing mechanism within a cybernetic framework for production systems

Christina Reuter, Timo Nuyken, Bartholomäus Wolff
RWTH Aachen University
Laboratory for Machine tools and Production Engineering (WZL)
b.wolff@wzl.rwth-aachen.de

Abstract
The paper introduces a conceptual research framework for self-optimizing logistical systems combining deterministic models of production logistics and shop floor management within a cybernetic control loop model.

Keywords: Self Optimization, Cybernetics, Production Theory, Logistics

Introduction

The dichotomy of planning-orientation versus value-orientation

The so called polylemma of production consists of two dichotomies (figure 1): firstly the dichotomy between economies of scale and economies of scope and secondly the dichotomy between planning orientation and value orientation (Brecher 2011).

According to Porter (1998) there are two mutually exclusive strategies to position a company within the first dichotomy. A scale orientated production company focuses on cost leadership trying to reach low costs per unit with a standardized product spectrum and highly automated production resources. In contrast a scope oriented production company focuses on quality leadership. Hereby, production resources and organizational structures are designed to enable a production of customized products. Current technological progress in the development of additive manufacturing processes like selective laser melting or 3D printing offers an approach to reduce the dichotomy between economies of scale and scope allowing companies to produce customized products at low unit costs (Poprawe et al. 2014).

The dichotomy between planning orientation and value orientation will be addressed in the main part of this paper and will therefore be explained in detail in the next paragraph.

Planning oriented management approaches are characterized by sophisticated models of production systems trying to describe the interaction of as many relevant parameters as possible (Schmitt et al. 2011). A crucial pre-condition of such an approach is the transparency of the production processes that should be modelled. Since planning processes occur a priori they always map a current stationary condition of the system. Therefore the quality of planning processes relies strongly on continuous adjustments of the models which is time-consuming and cost intensive. Value oriented approaches in contrast are characterized by a shift of decision processes from indirect planning areas, which do not add direct value to a production process, to direct value-adding processes that are usually located on the shop floor level. Lean manufacturing principles with their goal to focus on pure value adding activities and reduce wasteful ones represent such an value oriented management approach. Its strength is a high degree of flexibility, since decision processes are often delegated to de-central units like shop floor teams. Further, planning activities are reduced to a minimal by introducing self-regulating, event driven control principles like the pull control. However, the drawback of pure value-orientation is that optimization potential remains unused due to a missing holistic view on the production system as it is the case in a planning oriented approach (Brecher 2011).

Companies have to combine the advantages of both strategies in order to reduce the trade-off between them. Therefore two expertise need to be developed: firstly, deep knowledge about the deterministic relationships within their technical and socio-technical value-adding processes in order to make them accessible to optimization models and secondly, adaptive behaving cybernetic organisational structures in order to enable an effective and flexible adjustment of target values based on real time data.

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In the following sections the paper introduces a cybernetic framework integrating planning-oriented modelling and simulation of logistical systems with value-oriented configuration of shop floor management. The concept is based on the principle of self-optimization as a generic strategy to reduce the dichotomy between planning and value orientation.

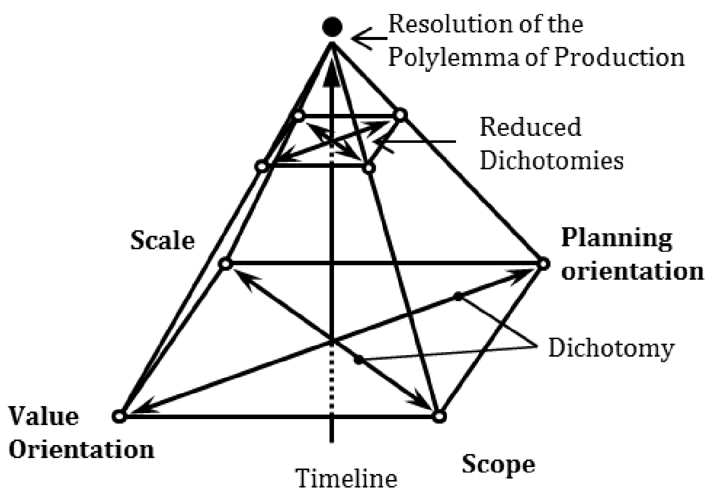

Figure 1 – The polylemma of production

Self-optimization as a generic strategy to reduce the dichotomy between planning-orientation and value-orientation

The implementation of self-optimizing abilities in production systems offers the possibility to reduce the trade-off between planning and value-oriented management since self-optimizing systems by definition are able to adjust their externally given goals situatively by the technical systems themselves (Pfeifer and Schmitt 2006; Chryssolouris and Mourtzis 2004). Since in even comparatively simple cases of automatization an independent change of its inner state cannot be achieved purely by a technological system, people have to be integrated into self-optimizing structures of production systems (Schmitt 2011). According to Adelt et al. (2008) a self-optimizing system is defined by the recurring execution of the following actions:

- continuous analysis of the current situation,
- determination of targets, and
- adaptation of the system's behavior to achieve these targets.

Such characteristics of self-optimizing systems allow to master processes with no existing closed deterministic control function as it is the case in networked logistical processes. Therefore self-optimizing systems are modelled with cybernetic control loops (see figure 2 right site). In a traditional control loop structure the systems behavior is controlled by external target parameters. If the control loop is able to adapt control parameters to observed changes it is called an adaptive system (Schmitt 2011). This concept of closed-loop control can be employed in various levels of an enterprise like control of technical processes on machine level or logistics on facility level (Takeda, 2009) (figure 2 left site).

The self-optimizing part of the control loop represents the value-oriented subsystem of the model, since it enables the analysis of the current situation within the control path and its flexible adjustment to changing conditions. The derivation of target values based on analysis and simulation of the system constitute the major planning-oriented aspects within the control.

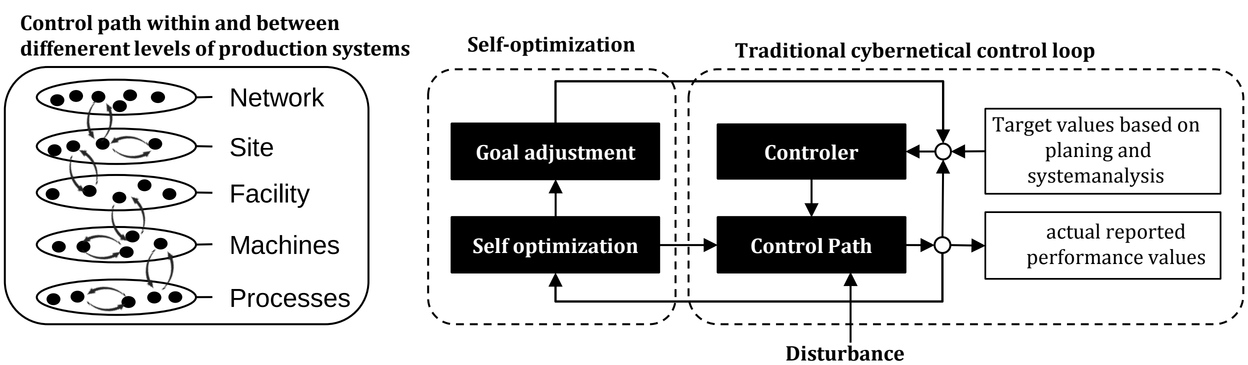

Figure 2 – Control loops within a production system (left), generic structure of a self-optimizing control loop (right) (see Schmitt et al. 2011)

In the following section we present an approach to operationalize and investigate the value oriented and planning oriented part of this control loop by adapting it to a logistical subsystem.

Approach

Cybernetic framework for self-optimization of logistical subsystems

In order to reduce the complexity of the model, the logistical control path is modelled as a black box containing all relevant resources and structures from machines level to the whole production site. The components of the control loop are described further.

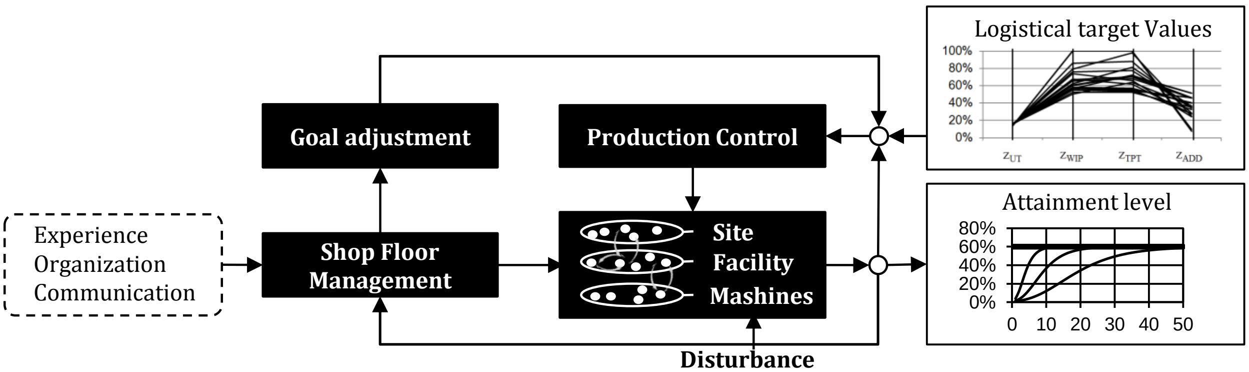

Figure 3 – self-optimizing control loop for logistical target values

The goal of the logistical system is to reach optimal logistical objectives. According to Nyhuis and Wiendahl (2009) the following four parameters state the crucial target or control parameters of the logistical control path:

- utilization (UT)
- work in process (WIP)
- throughput time (TPT)
- adherence to delivery dates (ADD)

The control unit is represented by a company's production planning and control activities. According to Lödding (2011) they are characterized by the following levers (table 1).

Table 1 – Levers and methods of production control

Levers of production control	Exemplary methods
Job creation	Event driven, periodic, …
Job release	Load dependent job release, stock controlling job release, job release according to target date, …
Sequencing	First in - first out, minimum slack, shortest processing time, longest processing time, …
Operational capacity management	Flexibility of operating resources (variation of amount, variation of intensity), Flexibility of staff (flexibility of working hours, flexibility in hiring and release) …

A combination of the different methods within each control lever leads to a specific production control configuration (PCC). Schuh et al. (2014) show that there is a theoretical performance limit concerning the logistic objectives which can be achieved by production control through variation of the PCC. This performance limit determine the target values for the control path. Its identification will be described in section 2.2.

The self-optimization unit in figure 3 is represented by a shop floor management unit. Based on the findings of Schuh et al. (2012) we model this black box by three major areas of influence: organization, communication and experience of the staff. A detailed description will be presented in section 2.3.

Both formal approaches, the modelling of the logistic objectives as well as the areas of influence on the performance of shop-floor management will be integrated into the following formal model that describes the dynamic behavior of the control path.

In order to operationalize the dynamic behavior of the performance development of a production system concerning the logistic objectives we adapt a learning curve model which is well established in manual assembly processes (Greiff 2001) and should serve as an approach to describe the dynamic of the discussed control loop.

Equation (1) describes the generic performance development of a learning socio-technical system according to the theory of Hull (Hull 1952) and the formalism of Noble (Noble 1957). In table 2 its parameters are explained and in figure 4 the corresponding graph is shown. The parameter a is the asymptote of the graph and corresponds to the performance limit of the system. In this case it represents the maximal attainment level of the logistical. The parameter s represents a measure for the initial performance of the system. The learning rate r of the system is a measure for the performance increase over time.

$$f(t) = a * s^{r^t} \tag{1}$$

Table 2 – Parameter description of the learning curve

Parameter	**Meaning**
a	Asymptote: theoretical performance limit of the system (0-1)
s	Initial performance value of the system (0-1)
r	Learning rate – measure for the performance increase over time (0-1)
t	time

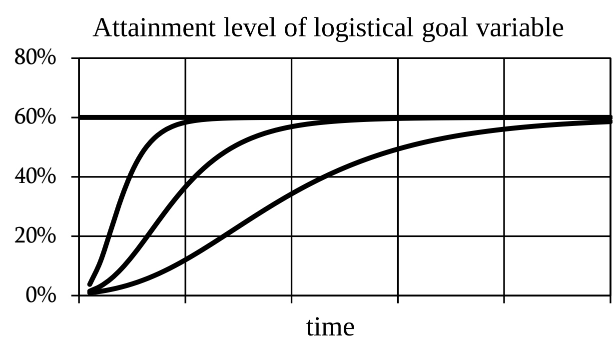

Figure 4 – Graph of the learning curve with varying learning rates

Theoretical performance limit *a* of production control concerning logistical objectives

The theoretical performance limit of a specific production structure concerning the logistical goal variables is analyzed by Schuh et al. (2014) and can be described by equation (2).

$$a = max_{PCC} \sum_{i=1}^{4}(w_i * z_i) \quad with\ i = \{UT; TPT; WIP; ATD\} \tag{2}$$

The determination of the performance limit is the result of an optimization problem in which the production control configuration (PCC) is systematically varied in order to maximize the weighted (w_i) sum of the attainment level of the logistic objectives z_i utilization, throughput time, work in progress and adherence to delivery date based on real production data. Since the logistic objectives compete against each other and cannot be maximized simultaneously it is necessary to introduce weighting coefficients which need to be determined according to current preferences of the company.

Figure 5 depicts the result of a simulation run of the achievement level of all logistic objectives for different production control configurations. Work in progress and through-put-time are scaled relatively to a company specific reference value in order to be integrated on the percental scale between 0 and 100 %. In this special case the maximal weighted total target achievement that can be reached is about 45 %. The corresponding values of the logistic objectives state the targets values for the modelled domain of the production system.

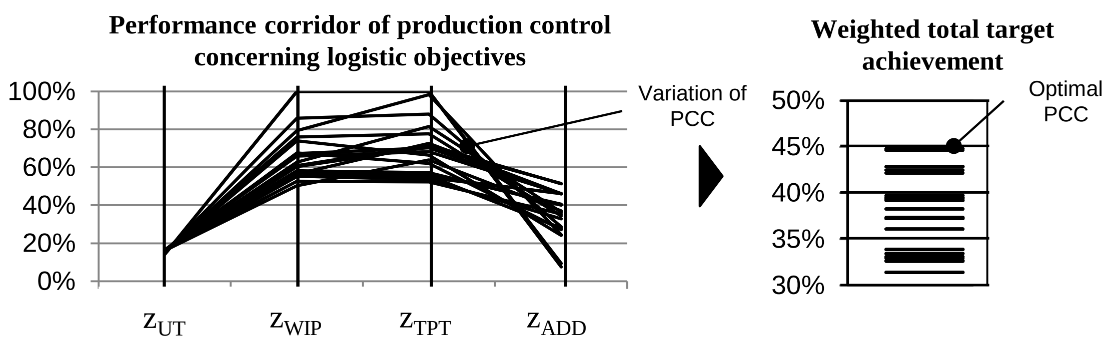

Figure 5- simulation of total target achievement of logistical goal variables

Model of the learning rate *r* for the context of shop floor management

Learning rates are well investigated for manual assembly processes and typically modelled as a function of the cumulated number of produced units. Major influencing variables on the productivity of such processes are the worker experience, the amount of repetitions and task specific factors like degree of difficulty or amount of manual tasks (Greif 2001). Learning in the context of production management activities like shop floor management, or maintenance contains a broader spectrum of learning relevant influencing factors than a repetitive process like assembly. In order to operationalize the learning rate of a shop floor management unit we refer to a model of Schuh et al.(2012) from the context of maintenance and adapt it to the context of shop floor management. According to Schuh et al. (2012) the following three major areas of influence need to be taken into account in order to model the performance of shop floor management teams:

- Staff experience and responsibility structure (*SE*)
- Organizational effects (*OE*)
- Communicational effects (*CE*)

This leads to a general model of the learning rate for a shop floor management unit according to equation (3).

$$r = r_{SE} * OE * CE \tag{3}$$

Hence, the learning rate is determined by a term which describes the expertise of the involved staff r_{SE} and two factors considering organizational and communicational conditions. According to Schuh et al. (2012) the first term is formalized by the following equation (4).

$$r_{SE} = 1 - c_1 * \left(\frac{f}{SR}\right)^{c_2} \tag{4}$$

The parameter f within (4) represents the amount of process interventions or interactions between an employee and an technological or logistical process and is a measure for the process understanding of employees. This term corresponds with the basic relationship of learning rates that a repetitive execution of tasks leads to growing process expertise of the executing person. In shop floor managements this corresponds to the lean management principle of “go to gemba” which demands the regular interaction with the process problems.

In contrast to this, the term *SR* leads to a decrease of r_{SE}. It represents the amount of employees which are responsible for an area of the production system or a process chain. The idea behind the term is that a growing division of labor respectively broader distribution of responsibility for specific process chains leads to a decrease of specialized or deep understanding of individual employees which leads to a decrease of economies of scale due to a loss of specialization. A reduction of SR corresponds with the lean management principle of job enlargement and job enrichment.

Finally, the parameters c_1 and c_2 state degrees of freedom in order to fit the function to company specific conditions.

Based on the model of Schuh et al. (2012) and a consortial benchmark study with focus on best practices in production systems (Schuh et al. 2012a), the coefficient *OE* is operationalized through the span of control within production management teams. Insights of the benchmark study show that successful shop floor management teams keep the span of control at low level of about eight to ten employees. Communicational cascades which can range from worker level up to the side manager are typical communicational structures within shop floor management teams. There effectiveness have a crucial impact on the performance of shop floor management teams. The higher the hierarchical distance that needs to be passed the longer the decision processes which has a negative impact on the reactivity and the performance of a shop floor management. Therefore hierarchical distance is taken as a measure for the communicational effect *OE* in equation (3). These consideration are formally modelled by equation (5), in which the parameter *s* represents the span of control and the parameter *h* the hierarchical distance in communication cascades. As in equation (4) the parameters c_3 and c_4 are constants that need to be fitted to company specific conditions through quantitative investigations.

$$OE * CE = \frac{c_3}{s} * \frac{c_4}{h} \tag{5}$$

Conclusions and future research

In order to reduce the dichotomy between planning-orientation and value orientation companies need to understand the advantages and design levers of both approaches. The concept of self-optimization states an generic approach to reduce the dichotomy. However, systematic conceptualization for production systems are scarce. The paper presents a concept how to operationalize two crucial aspects of self-optimization for a logistical systems, the determination of targets as well as the adaption of the system's behavior to achieve these targets.

The performance limit of the production control determines the target achievement level concerning the logistic objectives. A production control unit should therefore identify these limits for its production structure in order to derive realistic target values for the logistical system. Since such results always state a theoretical goal the adaption of the system's behavior to reach them or to adjust them needs self-functional function in form of shop floor management. The staff experience, the organizational and communicational structure state three major design levers for an effective shop floor management which companies need to consider in their production management. The paper presented a concept to formalize these levers. This first qualitative approach needs to be verified in further investigations in order to generate quantitative insights into the postulated relationships.

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Bibliography

Adelt, P., Donoth, J., Gausemeier, J. 2008. Selbstoptimierende Systeme des Maschinenbaus – Definitionen, Anwendungen, Konzepte.. In:Gausemeier J, Rammig F, Schäfer W (eds) HNI-Verlagsschriftenreihe, vol 234. Westfalia Druck GmbH, Paderborn

Brecher, C. 2011. Integrative Production Technologies for High Wage Countries. Springer Verlag, Heidelberg: 20-23

Greiff M.. 2001 Die Prognose von Lernkurven in der manuellen Montage unter besonderer Berücksichtigung der Lernkurven von Grundbewegungen. VDI Verlag, Düsseldorf 2001: 41ff

Hull, C.L. (A behaviour system) 1952; An introduction to behavior theory concerning the individual organism. New haven, CT; Yale University Press.

Noble, C. E. (The length-difficulty relationship in compound trial-and-error learning) 1957: The length-difficulty relationship in compound trial-and-error learning, In: Journal of Experimental Psychology, 1957, 54. Jg., Nr. 4, S. 246-252.

Lödding, H. 2011. Handbook of Manufacturing Control. Springer Verlag, Heidelberg: 95ff

Noble, C.E. (The length- difficulty relationship in compound trial-and-error learning) 1957 In: Journal of

Experimental Psychology, 1957, 54. Jg., Nr. 4, S. 246-252.
Nyhuis, P., Wiendahl, H.-P. 2009. Fundamentals of Production Logistics. Springer Verlag, Heidelberg.: 10
Pfeifer, T., Schmitt, R. 2006. Autonome Produktionszellen: Komplexe Produktionsprozesse flexibel automatisieren. Springer Verlag, Berlin.
Poprawe R., Hinke, C., Meiners, W., Schrage, J., Bremen, S., Merkt, S. (2014): SLM Production Systems: Recent Developments in Process Development, Machine Concepts and Component Design. In: Advances in Production Technology 2014, Springer:49-68
Porter, M.E. 1998. Compettive Strategy. Free Press
Schmitt et al. (2011): Self-optimising Production Systems. In: Integrative Production Technologies for High Wage Countries, Springer (2011):752-789
Chryssolouris, G, Mourtzis, D, Autonomous control of processes. In: Scholz-Reiter, B., Windt, K., Kolditz, J., Böse, F., Hildebrandt, T., Philipp, T., Höhns, H. 2004. IFAC conference manufacturing, modelling, management and control. Elsevier Science, Amsterdam
Schuh, G., Potente, T., Bachmann F., Froitzheim, T. (2012): An ingegrated approach – combining process management, organizational structure and company layout. In: Robust Manufacturing Control- Proceedings of the CIRP Sponsored Conference RoMaC 2012, Bremen, Germany, 18th-20th June 2012: 4811-494
Schuh et al. (2012a) Konsortial Benchmark Production Systems, WZL RWTH Aachen University
Schuh, G. 2014. Approach to assess and compare the performances of production structures. Apprimus Wissenschaftsverlag, Aachen: 217
Takeda H (2009) QiP – Qualität im Prozess: Leitfaden zur Qualitätssteigerung in der Produktion. Finanz Buch Verlag GmbH, München