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Autonomously controlled production systems—Influence of autonomous control level on logistic performance

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ABSTRACT

Autonomous control intends to improve production systems performance by distributed and flexible coping of complexity. Different autonomous control levels and control strategies are evaluated. The evaluation system benchmarks the level of logistic target achievement related to the level of complexity and the level of autonomous control. Based on real production data, simulation models were built. The level of autonomous control in these models is increased stepwise by expanding the number of autonomously controlled elements. For each level of autonomous control, three control strategies are implemented and compared to the performance of conventional control.

1. Introduction

Manufacturing companies are confronted with high complexity in combination with constantly changing process parameters. Over the last years, customers increasingly demand highly customized products, a reduction in delivery times and due date punctuality. Manufacturing enterprises have to rapidly adapt to these changes. These highly dynamic and complex conditions cannot be handled with current production planning and control methods [1].

The implementation of decentralized control, e.g. autonomous control coming from self-organisation theory, opens new potentials to cope with the new demands in logistic processes. Autonomous control in logistics represents a new field of research and is characterised by the ability of logistic objects (e.g. order, pallet, and machine) to process information in order to make and execute decisions on their own [2].

Implementation of autonomous control may increase the robustness of a logistic system against external and internal disturbances by influencing the behaviour of the system in a positive manner. Furthermore, it has been shown that autonomous control methods can help improve the logistic performance of production systems [3].

An evaluation system is introduced here that measures the performance of autonomous control. Furthermore, different simulation models with different levels of autonomous control and different levels of dynamic complexity are investigated and compared to the performance of conventional control. Basis for the simulation models are real production data of a power plant supplier.

2. Concept and evaluation of autonomous control

The vision of autonomously controlled logistic processes is characterized by the shift of qualified capabilities from the total system to its elements. Motivation and hypothesis in this context is that while increasing the systems complexity, implementation of autonomous control leads to an improved achievement of logistic targets.

The achievement of logistic targets in dependence of the level of autonomous control and the level of complexity of the considered logistic system provides the basis for measuring the logistic potential of autonomous control. To determine the application potential and the limitations of autonomous control shown in Fig. 1, an evaluation system has been developed to measure the logistic target achievement, the level of complexity and the level of autonomous control. Basis for the shape of the curve are the following assumptions: in highly complex systems, the achievement of logistic targets will increase with the level of autonomous control until reaching a specific level of autonomous control. Conventional planning and control methods with a low level of autonomous control enable high achievement of logistic targets in systems with a low level of complexity, but while increasing the systems complexity the logistic target achievement decreases. The highest level of autonomous control will in general result in a low achievement of logistic targets. In this case, the system behaviour will lead to anarchy, which does not ensure the achievement of global goals [4].

The following passages describe briefly the determination of the three axes in Fig. 1, which is presented more detailed in [5–7]. In the context of engineering science the operationalisation of systems complexity is a task with a wide range of approaches in research [8]. Because these approaches refer to specific aspects of complexity, as for instance process or product complexity [9], an entire understanding of the term complexity in the context of logistic systems is necessary. In order to obtain a comprehensive description of the complexity of a production system, it is essential to define different categories of complexity and to refer them to each other as shown in [5]. In consequence, three views of complexity with distinction between static and dynamic parts, structural and process-related parts as well as internal and

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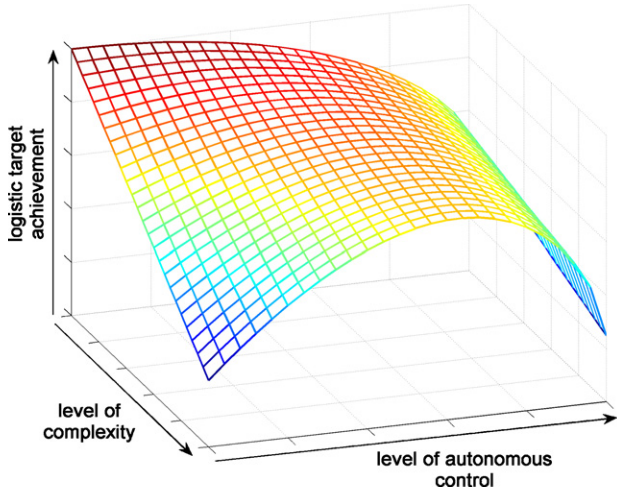

Fig. 1. Correlation between logistic target achievement, level of complexity and level of autonomous control [2].

external parts of complexity were derived and referred to each other. It is obvious that complexity cannot be described by a single number but by sets of multiple factors. These parameters of complexity can be assigned to the relevant categories and described by vectors. So far, it is possible to detect a complexity difference of two considered systems. Consequently, the complexity axis in Fig. 1 represents an ordinal scale. Furthermore, it is possible to compare either single parameters, complexity categories or combinations of categories, for example, the dynamic internal structural complexity.

To measure the level of autonomous control a catalogue of criteria was developed [6]. This catalogue is based on a morphological scheme for characterising structures of order processing. Furthermore, the catalogue is classified in layers of organisation and management, information and communication technologies as well as in material flow and logistics. These layers relate to decision, information and execution systems. The definition of autonomous control explained above describes the maximum level of autonomous control where all system elements are able to interact with other system elements and make decisions on the basis of an inherent, decentralized target system. In general, logistics systems contain both conventionally managed and autonomously controlled elements and it is assumed that there are different levels of autonomous control.

The catalogue of criteria consists of 13 criteria as well as corresponding properties with an increasing level of autonomous control in their order from left to right. An example for a criterion is “location of decision-making” where a logistic system with decentralised decision-making by its elements has a higher level of autonomous control than a system rendering central decisions. Each property of a criterion contains a fulfilment value, which is distributed in the range of 0 (absolutely conventionally controlled)–3 (absolutely autonomously controlled). In combination with weightings for each criterion it is possible to measure the level of autonomous control in percentage.

Basis for concrete measuring of the degree of logistic target achievement and the evaluation of alternatives is a vectorial approach with logistic target vectors **z** as shown in the following form [7]:

$$\mathbf{z} = \begin{bmatrix} \textit{Due date reliability} \\ \textit{Through put time} \\ \textit{Utilization} \\ \textit{Work in process} \end{bmatrix}$$

This format of the vector applies to target vectors as well as to vectors with actual values, which are used to determine the logistic performance figures and to evaluate logistic objects and decision alternatives. In order to consider different weights of logistic objectives a weighting vector γ is introduced. The target value vectors of logistic objects contain the desired values for the individual logistic objectives. By comparing the target value $\mathbf{z}_{\text{target}}$ with the actual value vector $\mathbf{z}_{\text{actual}}$ it is possible to convert the originated vector $\Delta\mathbf{z}_{\text{target-actual}}$ in a vector **e** with the degrees of individual logistic achievement objective:

$$\Delta\mathbf{z}_{\text{target-actual}} \Rightarrow \mathbf{e} = \begin{bmatrix} e_{\textit{Due date reliability}}[\%] \\ e_{\textit{Through put time}}[\%] \\ e_{\textit{Utilization}}[\%] \\ e_{\textit{Work in process}}[\%] \end{bmatrix}$$

with $e_{\text{Due date reliability}}$, $e_{\text{Throughput time}}$, $e_{\text{Utilization}}$ and $e_{\text{Work in process}}$ as degrees of logistic target achievement for each individual objective in [%].

The determination of the degree of logistic target achievement takes place by normative-actual value comparison of the respective objective considering a given distribution of actual values and target achievement for each logistic object. Each logistic object additionally contains a weighting vector γ for its logistic goals. The scalar product of γ and **e** represents the achievement of goals for individual objects. Calculating the weighted average of all logistic objects will lead to the logistic target achievement for the global system [7].

3. Autonomous control methods and production scenario

Next, the real production scenario and the applied autonomous control methods will be presented. Therefore, Section 3.1 briefly outlines the concept of the applied autonomous control methods. Section 3.2 describes the characteristics of the production scenario and the implementation of different complexity levels, respectively, of different autonomous control levels.

3.1. Autonomous control methods

Three autonomous control methods are modelled: a queue length estimator method (QLE), a due date method (DUE) and a pheromone-based approach (PHE). All methods enable autonomous decision-making for parts running through the production system. Intelligent parts using the QLE method pursue the objective to reduce their own throughput time (TPT). To meet this objective, parts are able to choose a workstation for processing: a part enters a work system with parallel and technologically substitutable workstations. It compares the buffer level of each workstation and chooses the one with the lowest workload for further processing [3,10]. The DUE method is based on the QLE method, it also enables parts to compare their given due dates with an estimated due date. Parts using this method will choose the workstation, where the variation of planned and estimated due date is the smallest [10].

The pheromone approach (PHE) is inspired by a biological process. It imitates the process of ants marking possible routes to food sources with pheromone trails. Succeeding ants follow the pheromone trail with the highest concentration [11]. To transfer this process, parts leave information about their TPT at each machine. Parts arriving later at a certain stage of the shop floor compare these artificial pheromones by computing average TPT data of the last five parts and then choose a line. Hence, the pheromone concentration depends on waiting and processing times of previous jobs. The evaporation process of natural pheromones is modelled by using a moving average of pheromone TPT data. Similar approaches for modeling pheromone-based autonomous control methods can be found in [12,13].

3.2. Production scenario

A simulation model of a power plant supplier, based on real production data is considered. The production process in this study involves 19 work systems, containing overall 110 different workstations (Fig. 2). For production planning and control, the

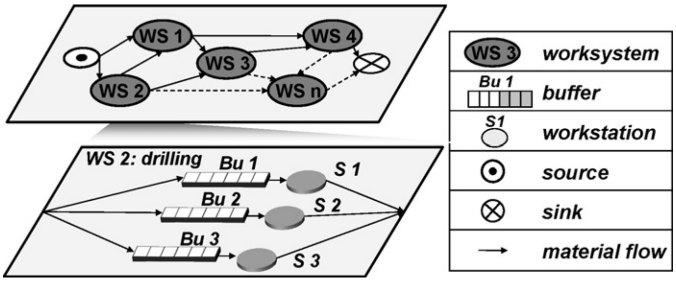

Fig. 2. Structure of the production system.

company uses a common PPC system, which is well adapted to its requirements and which focuses in particular on the reliability of due dates.

Regarding the 19 work systems, a set of experiments that gradually increase levels of autonomous control and rising levels of complexity was designed. Four work systems with 22 workstations, which are parallel and technologically substitutable, were selected to implement the autonomous control methods (QLE, DUE and PHE). To model an increasing level of autonomous control (ACL), the number of autonomous controlled work systems is increased stepwise in different simulation runs. Remaining work systems are controlled conventionally (CP) and use the preplanned data of the PPC system to assign orders to machines. An increase of dynamic complexity is modelled in a similar way. As described before, the complexity of systems can be classified by a set of parameters. In this case, all parameters (e.g. number of machines and number of orders) are kept constant except the number of machine breakdowns. Therefore, machine availability as a parameter for internal structural dynamic complexity is reduced to four steps by the implementation of stochastic machine breakdowns. These breakdowns occur according to a random uniform distribution and cause reduced machine availability in steps of 5% from 100% to 85% in different simulation runs. These different machine availabilities are here defined as complexity level (CL). Four different complexity levels will be investigated (CL 1–CL 4).

There are two order types in this production scenario: stock orders and customer orders. Customer orders are directly linked to requests of customers and have a higher priority regarding due date punctuality. For this reason, different target priorities exist for each order type: stock orders have a high priority in the reduction of TPT, customer orders aim additionally at due date punctuality. To take these different logistic objectives into account, the measurement and evaluation of logistic performance will be done by a vectorial approach as shown above. In this respect, the objectives throughput time and adherence of due dates are used and weighted with predefined weight vectors γ_s for stock orders and γ_c for customer orders:

$$\boldsymbol{\gamma}_s = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}; \qquad \boldsymbol{\gamma}_c = \begin{bmatrix} (1-\alpha) \\ \alpha \\ 0 \\ 0 \end{bmatrix}$$

The γ_c vector comprises two elements, which weight the TPT (α) and the adherence to due dates ($1-\alpha$). In total, the sum of each weight factor element has to be 1. Thus the factor α predetermines the weight of TPT, and adherence to due dates, respectively. Varying α allows to consider different objective priorities. This factor α is varied to evaluate the autonomous control methods and to analyse their performance with respect to different priorities of objectives. By computing $\Delta\mathbf{z}_{\text{target-actual}}$ out of the original PPC and the simulation data, the relative target achievement **e** of each job is determined and will finally be weighted by calculating the scalar product of **e** and the corresponding vectors γ_s and γ_c. The weighted mean value of the relative target achievement of all jobs determines the relative target achievement of the total system.

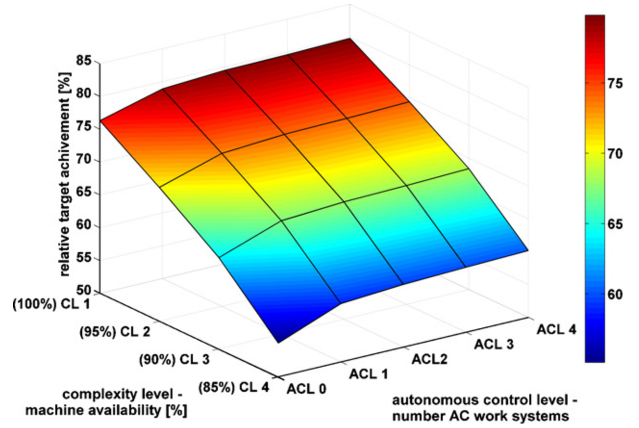

Fig. 3. Relative target achievement of QLE method.

4. Simulation and results

The results of the discrete event simulation study concerning the impact of increasing autonomous control and complexity levels will be presented in the following. Section 4.1 focuses on the relative target achievement of the QLE, DUE and PHE method for a certain $\alpha = 0.4$. The impact of the weight factor α will be investigated in Section 4.2 by analysing the methods performances for varying α.

4.1. Impact of autonomous control and complexity level

Fig. 3 presents the relative target achievement of the QLE method. Each grid point in Fig. 3 represents a simulation run with a certain level of autonomous control and dynamic complexity. In this context, an autonomous control level of zero represents conventional control according to the original PPC data. Fig. 3 shows that the theoretically predicted effects in Fig. 1 can be observed in this real production data based scenario: an increase of the autonomous control level leads to a rising relative logistic target achievement for each complexity level.

Especially higher complexity levels underline the effect of an increasing autonomous control level. A comparison of the target achievement for CL1, respectively, CL4 clarifies that. An increase of autonomous control levels lead to an improvement of 3.5% for CL1. The target achievement for CL4, however, is improved by 5.04% with rising autonomous control level.

That implies that the QLE method affects the systems ability to cope with increasing dynamic complexity in a positive manner.

Table 1 summarizes the results of relative target achievement for all methods. It reveals a similar trend of relative target achievement for the DUE method concerning the impact of

Table 1
Relative target achievement of all methods.

	Relative target achievement (%)				
	ACL 0	ACL 1	ACL 2	ACL 3	ACL 4
QLE					
CL1	76.3116	78.889	79.4542	79.5765	79.8093
CL2	70.3797	73.2958	73.9339	74.108	74.3675
CL3	63.907	67.2689	67.874	68.1049	68.4095
CL4	55.1354	58.8726	59.5491	59.885	60.1754
DUE					
CL1	76.3116	78.8806	78.4598	78.6447	78.6447
CL2	70.3797	73.2881	73.0093	73.2885	73.5335
CL3	63.907	67.2638	67.1201	67.293	67.5458
CL4	55.1354	58.8448	58.9504	59.3279	59.5623
PHE					
CL1	76.3116	78.0284	77.7493	77.6524	77.5741
CL2	70.3797	70.3797	72.0016	71.8127	71.8365
CL3	63.907	66.1234	65.8681	65.6076	65.5871
CL4	55.1354	57.5373	57.4244	57.2946	57.3083

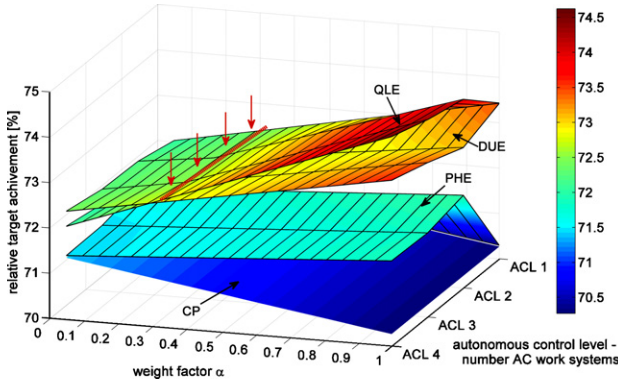

Fig. 4. Impact of weight factor γ_c.

increasing complexity and autonomous control level, but absolute values differ.

Although the DUE method uses information about due dates of orders, it leads to an approximately 0.48% lower performance than the QLE method. According to the weight vectors γ_s and γ_c it was expected that this method generates better results than the QLE method. This effect can be explained by the applied weight factor γ_c: the QLE method decreases the TPT more than it causes a variation in due dates. Consequently, the QLE method, even when the TPT weighs less ($\alpha = 0.4$) than adherence to due dates ($1 - \alpha = 0.6$), performs better than the DUE method in this case.

Table 1 also shows the results of the PHE method. Its performance as compared to the QLE and the DUE method is in average 1.68%, respectively, 1.19% lower. That indicates, that the usage of this method is not appropriate for the target priority of $\alpha = 0.4$.

4.2. Impact of weight factors

To understand the impact of the weight factors, Fig. 4 depicts the results of the QLE, DUE and PHE methods at complexity level CL2 for varying values of the γ_c vector. Fig. 4 also presents the results of the conventional planned (CP) scenario in form of a transparent plane to provide a better comparability of all methods. Notice that $\alpha = 1$ means that the weight of TPT is 100%, respectively, causes $\alpha = 0$ a TPT weight of 0%.

The target achievement of the QLE method rises with increasing α, as well as for increasing autonomous control levels. The QLE aims at reducing TPT, thus the target achievement rises in cases of a heavier weighting of the TPT. The DUE method follows a similar trend regarding the influence of α, but its relative target achievement is lower for $\alpha > 0.25$. In contrast to this, the DUE method leads to a better performance for $\alpha < 0.25$ (highlighted by arrows in Fig. 4). Below $\alpha = 0.25$ the weight of due date punctuality is strong. Hence each violation of the planned due date is punished by a low value of target achievement and the DUE method performs better than the QLE method. Fig. 4 indicates that both methods (QLE and DUE) are suitable for this scenario. The choice of a certain method depends on the global systems objectives. If due date punctuality has a high priority ($\alpha < 0.25$) the employment of the due date method is adequate. In cases of a higher priority of throughput time reduction ($\alpha > 0.25$), the QLE should be applied. In contrast to this, the PHE method performs worse, independent of the autonomous control level or the weight factor α. For these reasons, the application of the QLE or the DUE method seems to be more suitable than implementing the PHE method.

Fig. 4 additionally shows the results for the conventional control. Its performance rises slightly with decreasing α, due to its primary objective the improvement of due date punctuality. The target achievement of the conventional and the autonomous control methods differs less for heavier weighting of the due dates. Nevertheless, in the particular case of CL2, which is focused in Fig. 4, the autonomous control methods perform better.

5. Summary

This paper investigated a simulation model, based on real production data, with varying autonomous control and complexity levels. Summarizing the results of the previous section shows that all applied autonomous control methods behave similar regarding the impact of both factors. For each complexity level an increase of the autonomous control level improved the logistic performance. This effect enhances with rising complexity levels, which implies that autonomous control improves the handling of dynamic complexity in the particular scenario. These tendencies generally confirm the theoretical findings and the hypothesis presented in Section 2 concerning the impact of increasing complexity and autonomous control level.

Furthermore, it has been shown that logistic performance measurement by a vectorial approach is an adequate instrument to measure the achievement of multiple logistic objectives. The evaluation of autonomous control methods using this approach revealed that the QLE and the DUE method can be applied to different target priorities. The QLE method is applicable for a high priority of TPT reduction, whereas the DUE method performs best for a high priority of due date punctuality. Future research will focus on new bioinspired control methods, e.g. bacterial chemotaxis, and the corresponding system behaviour under complex conditions.

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