4.2 Evaluation of Autonomous Logistic Processes – Analysis of the Influence of Structural Complexity

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4.2.1 Introduction

The concept of autonomous control requires on one hand logistic objects that are able to receive local information, process these information, and make a decision about their next action. On the other hand, the logistic structure has to provide distributed information about local states and different alternatives to enable decisions generally. These features will be made possible through the development of Ubiquitous Computing technologies (Fleisch et al. 2003).

The application of autonomous control in production logistics can be realized by recent information and communication technologies such as radio frequency identification (RFID), wireless communication networks etc. These technologies enable intelligent and autonomous parts and products to communicate with each other and with their resources such as machines and transportation systems and to process the acquired information. This leads to a coalescence of material flow and information flow and allows every item or product to manage and control its manufacturing process autonomously (Scholz-Reiter et al. 2004). The coordination of these intelligent objects requires advanced planning and control concepts and strategies to realize autonomous control of logistic processes. To develop and analyze such autonomous control strategies dynamic models are required.

In order to prove that the implementation of autonomous control in production systems is more advantageous than conventionally managed systems, it is essential to develop an adequate evaluation system. This system reflects the degree of achievement of logistic objectives related to the level of autonomous control and the level of complexity. Within the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes: A

Paradigm Shift and its Limitations" at the university of Bremen (CRC 637) it is investigated in which case the implementation of autonomous control is superior to other approaches and where the limits are (figure 4.1 upper right).
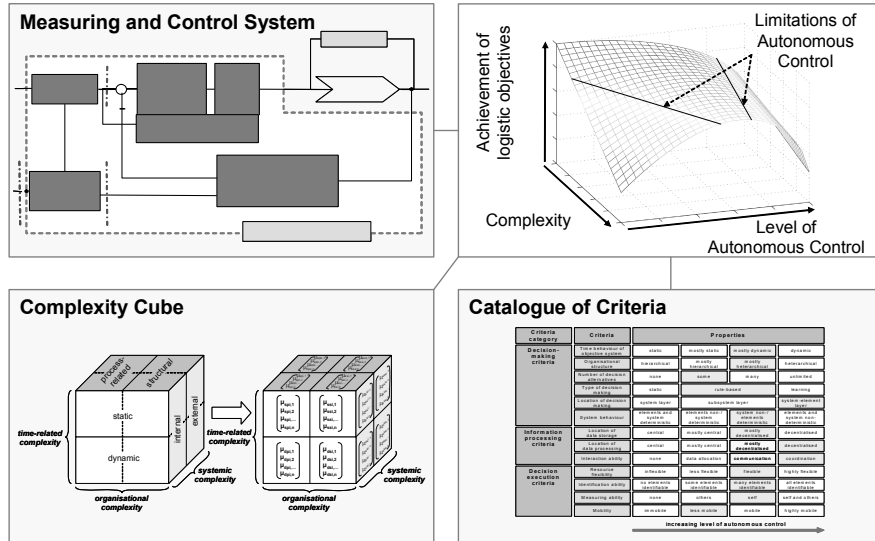

Fig. 4.1 Components of the evaluation system and limitations of autonomous control

In order to determine the limits of autonomy, the axes in the upper right curve in figure 4.1 have to be operationalised. The correlation between logistic objective achievement and level of autonomous control is heavily dependent on the complexity of the considered system. For the measurement of the logistic objective achievement a measure and controlsystem for logistic performance was developed. Furthermore a complexity cube was developed in order to characterize the complexity of production systems and a catalogue of criteria can be used to determine the level of autonomous control. Dynamic models and simulation studies can help to verify the run of the surface build by the single curves and thus the limits of autonomy can be found.

This article will first give a global definition of the term autonomous control in the context of the Collaborative Research Centre as well as a definition in the context of engineering science. Furthermore an approach to measure the complexity of production systems by dint of vectors and a

complexity cube is given. In order to measure the achievement of logistic objectives a feedback loop for autonomous processes together with a vectorial approach is introduced. This forms the basis for simulation studies of different autonomous control strategies. Two control methods are analysed in more detail with different levels of complexity of the considered production system in order to verify the hypothesis that autonomous control is a suitable approach to cope with increasing complexity.

4.2.2   Autonomy in production logistic

Based on this global definition of the term autonomous control which is described in chapter 1.1 a definition in the context of engineering science was developed, which is focused on the main tasks of logistic objects in autonomously controlled logistics systems:

"Autonomous control in logistics systems is characterized by the ability of logistic objects to process information, to render and to execute decisions on their own."(Windt et al. 2007)

The paradigm shift expressed in the definition is based on the following assumption: The implementation of autonomous logistic processes provides a better accomplishment of logistic objectives in comparison to conventionally managed processes despite increasing complexity. In order to verify this statement, it is necessary to characterize production systems regarding their level of complexity during the development of an evaluation system.

4.2.3   Complexity of production systems

Existing approaches

The term complexity is widely used. Generally it does not only mean that a system is complicated. Ulrich and Probst understand complexity as a system feature where its degree depends on the number of elements, their interconnectedness and the number of different system states (Ulrich and Probst 1988). An observer judges a system to be complex when it can not be described in a simple manner. In this context Scherer speaks of subjective complexity. Furthermore, he distinguishes between structural complexity which is caused by the number of elements and their interconnectedness and dynamic complexity caused by feedback loops, highly dynamic and nonlinear behavior (Scherer 1998). Moreover, complexity can be un-

derstood as interaction between complicatedness and dynamics (Schuh 2005).

An enormous challenge occurs during the operationalization of complexity in the form of a quantifiable complexity level. Some approaches to measure complexity use the measurement of entropy as basis (Deshmuk et al. 1998; Frizelle 1998; Frizelle and Woodcock 1995; Sivadasan et al. 1999; Jones et al. 2002; Karp 1994; Gellmann and Lloyd 1994). In thermodynamic systems entropy can be deemed to be the degree of disorganization of the considered system. Shannon and Weaver developed an equation to measure the amount of information on the basis of the equations for entropy measuring (Shannon and Weaver 1949). This can be used for complexity measurement because the more complex a system is, the more elements and relations are included and the more information is necessary to describe the system. Those considerations were adopted by Frizelle and Woodcock to develop equations to measure complexity in production systems based on the diversity and uncertainty of information within the system (Frizelle and Woodcock 1995). They defined the structural complexity as the expected amount of information necessary to describe the state of a system. In a manufacturing system, the data required calculating the structural complexity can be obtained from the production schedule. Frizelle and Woodcock defined the dynamic or operational complexity as the expected amount of information necessary to describe the state of the system deviating from schedule due to uncertainty.

It is obvious that complexity can not be measured by a single variable. It is necessary to describe complexity by multiple factors which are interdependent but can not be reduced to independent parameters (Schuh 2005). A various number of complexity measurements were developed in the research on complex networks, e.g., the internet (Amara and Ottino 2004) or biological networks (Barabasi and Oltvai 2004). In this context Costa et al. showed that a complex network can be represented by a feature vector (Costa et al. 2005).

This approach is seized for the description of complexity in the following (figure 4.2). By means of this vectorial approach it is possible to measure the complexity of production systems on an ordinal scale. Thus different systems are comparable and measurable concerning their level of complexity.
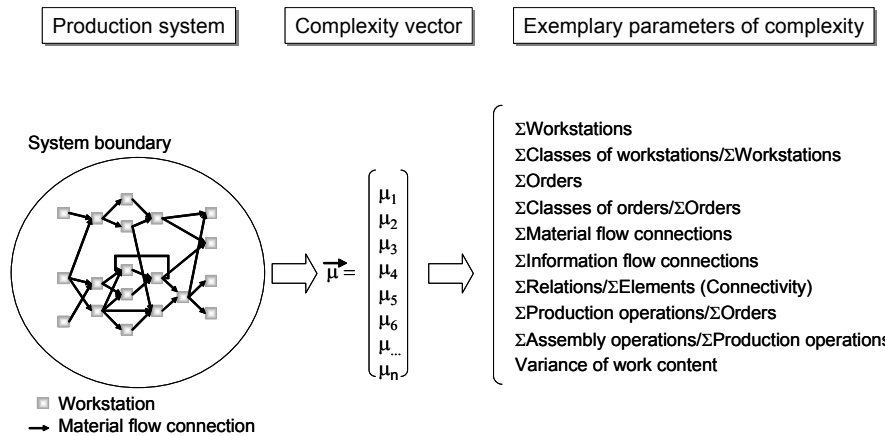
Production system   Complexity vector   Exemplary parameters of complexity

System boundary

$$\vec{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ \mu_5 \\ \mu_6 \\ \mu_{...} \\ \mu_n \end{bmatrix}$$

ΣWorkstations
ΣClasses of workstations/ΣWorkstations
ΣOrders
ΣClasses of orders/ΣOrders
ΣMaterial flow connections
ΣInformation flow connections
ΣRelations/ΣElements (Connectivity)
ΣProduction operations/ΣOrders
ΣAssembly operations/ΣProduction operations
Variance of work content

☐ Workstation
→ Material flow connection

Fig. 4.2 Characterization of a production system's complexity by a vector

The complexity of the total system is accordingly expressed by a complexity vector. In the first instance this vector is an approach to measure the different types of complexity in production systems which has to be specified in further research studies. Several parameters of the systems complexity are exemplarily represented in figure 4.2. By means of this approach it is possible to detect a $\Delta\mu$, which describes the complexity difference of two considered systems. In this manner the production system's complexity can be measured and consequently the effects of changing complexity levels can be analysed.

Complexity in the context of autonomous processes

As described in the chapter before there is a wide range of approaches to describe complexity of systems. Due to the fact that these approaches only refer to single aspects of complexity, as for instance the structure of a considered system, they seem insufficient for an entire understanding of the term complexity in the context of logistic systems, in particular production systems. As shown in (Philipp et al. 2006), it is essential to define different categories of complexity and to refer themselves to each other, to obtain a comprehensive description of the complexity of a production system. In consequence, three categories of complexity *time-related complexity*, *organisational complexity* and *systemic complexity* are derived and referred to each other in a complexity cube. They are defined as follows (Philipp et al. 2006).

Organizational complexity

Organizational complexity consists of process-oriented and structural complexity. Process-oriented complexity defines the number and diverseness of process flows whereas structural complexity describes the number and diverseness of systems elements, their relations and properties.

Time-related complexity

Time-related complexity is divided into a static and a dynamic component. Dynamic complexity characterizes changes with respect to number and diverseness of process flows, systems elements, their relations and properties in time dependent course. Compared to this, static complexity refers to a fix system status at a concrete point in time or in a concrete time period.

Systemic complexity

Systemic complexity deals with internal and external complexity and is determined by the system boundary. Process flows, system elements and their relations and properties which are assigned to the system are part of the internal complexity. Process flows, system elements, their relations and properties outside the system boundary belong to the external complexity.

These three categories of complexity, their characteristics and interdependences are illustrated in figure 4.3 in form of a complexity cube. As explained in chapter 3.1, each area of the complexity cube can be determined by a complexity vector. By defining each area of the cube, the complexity of any production system can be determined. Consequently, the complexity cube provides the opportunity to define and compare different levels of organisational, time-related and systemic complexity of several production systems.
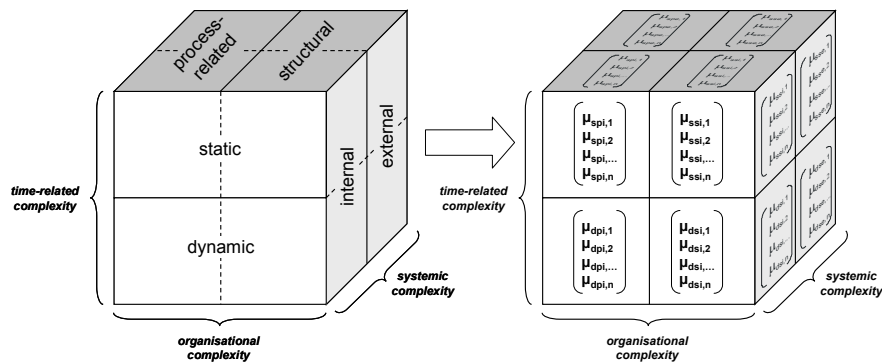

Fig. 4.3 Complexity cube for production systems (Philipp et al. 2006)

In order to get an idea how a specific vector for the different types of complexity looks like, an example for the structural static internal complexity is represented in the following:

$$
\vec{\mu}_{ssi} = \begin{Bmatrix}
\Sigma\text{Human actors} \\
\Sigma\text{Workstations} \\
\Sigma\text{Classes of workstations}/\Sigma\text{Workstations} \\
\Sigma\text{Orders} \\
\Sigma\text{Classes of orders}/\Sigma\text{Orders} \\
\Sigma\text{Material flow connections} \\
\Sigma\text{Classes of material flow connections}/\Sigma\text{Material flow connections} \\
\Sigma\text{Material backflows}/\Sigma\text{Material flows} \\
\Sigma\text{Information flow connections} \\
\Sigma\text{Classes of Information flow connections}/\Sigma\text{Information flow connections} \\
\Sigma\text{Relations}/\Sigma\text{Elements (Connectivity)}
\end{Bmatrix} .
$$

All parameters of this exemplary complexity vector are assigned to the production system (internal), can be determined at a concrete point of time or time period (static) and are referred to the systems elements, relations and properties (structural). According to Wiendahl et al. the human actors play an important role in mastering complex production systems. In this context we focus on human actors as resources and not on their specific individual behaviour (Wiendahl et al. 2005). There are basic parameters like the number of machines or the number of orders which must be included in the complexity vector but generally the choice of measurement parameters to determine the complexity difference of diverse production systems may vary and is highly dependent on the considered system.

4.2.4   Measurement and evaluation of logistic objektives

This chapter will focus on the measurement of the logistic performance of autonomous production logistic systems (e.g. a manufacturing system). Together with the measurement of the level of complexity explained in the previous chapter it allows an investigation of the coherence between the complexity and the performance of production systems.

Feedback loop of autonomous control

The basis for the measurement and evaluation of autonomously controlled logistic processes is a feedback control approach for individual logistic objects as shown in figure 4.4. Former approaches of control loops for production control are for example the works of Petermann and Breithaupt

(Petermann 1996; Breithaupt 2001). The difference of this approach is that the controlled system is the production process while in the works of Petermann and Breithaupt the controlled system was the work system.
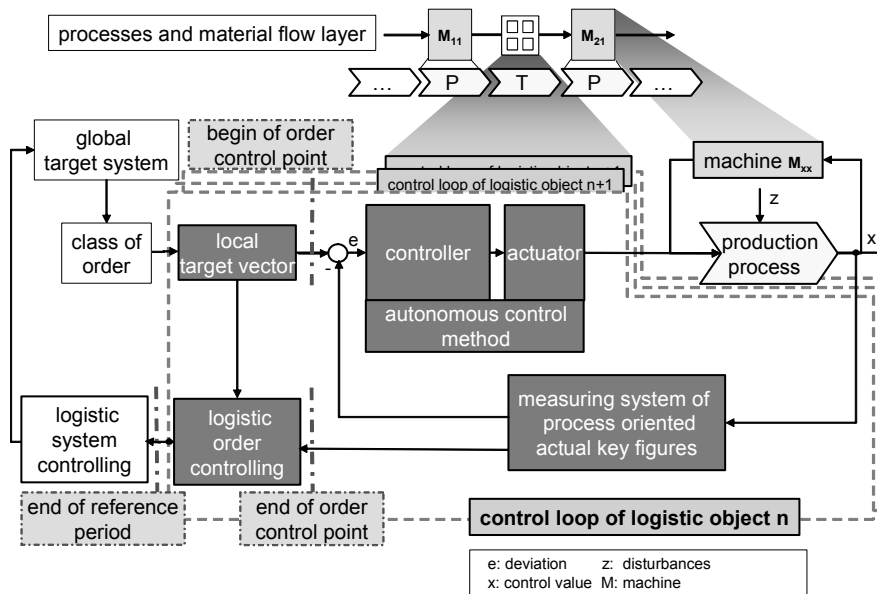

Fig. 4.4 Feedback loop of autonomous control (order view)

In this case the controlled process is a production process. Two logistic objects (an order as well as a resource) are involved in this process. Starting from a global system of objectives (the objectives of the considered production system), target values for varying object classes are deduced. This enables for example from an order's point of view a differentiation between customer orders and storage orders with different target weights for delivery reliability and throughput time of an individual order. Local objectives for individual logistic objects arise based on the object classes' objectives. These local objectives act as reference value for the feedback control approach for autonomously controlled processes. Eventual changes during the production process can immediately be realized through a fast feedback loop by measuring and calculating simultaneously the relevant logistic performance figures. Based on this feedback loop suitable solutions to react on process changes can be found by the evaluation of possible alternatives.

Within the controller (figure 4.4) the deviations of the production process from the local desired values are analysed. All possible alternatives to

react on the process deviation will be taken into consideration and are evaluated regarding its forecasted logistic performance. This first evaluation step provides the basis for the following operation procedures of a logistic object through the production floor.

The evaluation-based decision will subsequently be executed by the actuator. For example such a decision might be the change to a different machine if the object decides to change the manufacturing system because of a higher potential of the degree of logistic objective achievement. At the completion of a production order the actual logistic performance figures are immediately compared with the target performance figures (normative-actual value comparison). On this basis the degree of logistic objective achievement of an individual object is calculated. This represents the second step of the evaluation system.

By taking all objects within the entire system into account and in combination with weights of different objects it is possible to determine the degree of logistic objective achievement for the overall system at the end of a reference period for example. The weighting of individual objects or object classes allows to emphasize the importance e.g. of bottleneck machines or specific customer orders. The consideration of the overall system represents the third step of the evaluation system. Through the decentralized feedback control of individual objects an opportunity is given to react on eventual changes or disturbances near real time and thus to increase the logistic performance of the overall system while measuring the individual degree of logistic objective achievement.

Vectorial approach to measure the achievement of logistic objectives

The concrete measuring of the degree of logistic objective achievement and the evaluation of alternatives will be done by means of a vectorial approach. Basis for this approach is the logistic objective vector z as shown in the following form:

$$z = \begin{bmatrix} \text{Due date reliability} \\ \text{Throughput time} \\ \text{Utilization} \\ \text{Work in process} \end{bmatrix} \qquad (4.1)$$

This format of the vector applies for target vectors as well as for vectors with the actual values, which are used to determine the logistic performance figures to evaluate logistic objects and to evaluate decision alterna-

tives. In order to consider different weights of the 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 comparison of the target value z_{target} with the actual value vector z_{actual} it is possible to convert the thereby originated vector $\Delta z_{\text{target-actual}}$ in a vector e with the degrees of individual logistic achievement objective:

$$\Delta z_{\text{target-actual}} \Rightarrow e = \begin{bmatrix} e_{\text{Due date reliability}} \left[\% \right] \\ e_{\text{Throughput time}} \left[\% \right] \\ e_{\text{Utilization}} \left[\% \right] \\ e_{\text{Work in process}} \left[\% \right] \end{bmatrix} \tag{4.2}$$

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

The determination of the degree of logistic objective achievement takes place by normative-actual value comparison of the respective objective considering a given distribution, as shown in figure 4.5 using the example of due date variation.
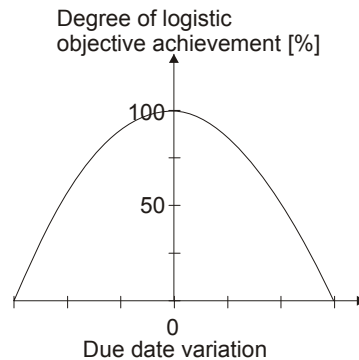

Fig. 4.5 Determination of degree of objective achievement

In this example a due date variation of zero days would lead to 100% objective achievement while a due date variation of two days would approximately lead to only 50% objective achievement. By means of distributions of this type it is possible to determine the logistic objective achievement through reading the difference of target value vector and actual value vector in this diagram. In a next step the achievements of all objectives are aggregated in one degree of logistic objective achievement for the individual object. This is done by introduction of the upper mentioned

weighting vector for an individual object. Thus a possibility is given to determine the degree of logistic objective achievement e_{obj} in [%] for an object by calculating the scalar product of weighting vector $\boldsymbol{\gamma}$ and the vector e with the individual degrees of objective achievement:

$$\text{e} \cdot \gamma = \begin{bmatrix} e_{\text{Due date reliability}} \left[\% \right] \\ e_{\text{Throughput time}} \left[\% \right] \\ e_{\text{Utilization}} \left[\% \right] \\ e_{\text{Work in process}} \left[\% \right] \end{bmatrix} \cdot \begin{bmatrix} \gamma_{\text{Due date reliability}} \\ \gamma_{\text{Throughput time}} \\ \gamma_{\text{Utilization}} \\ \gamma_{\text{Work in process}} \end{bmatrix} = e_{\text{obj}}[\%] \qquad (4.3)$$

In this case it is very important that the sum of all γ_i within the weighting vector is exactly one to get a proper result in a percentage rate. Consequently, this equation describes the second step of the evaluation system. For the third step of the evaluation system it is essential to aggregate the objects achievement of objectives in one degree of logistic objective achievement for the total system. For this reason it is necessary to implement weights for individual objects, which describe the effects of single objects on the total system. That means that all objects can provide different contributions for the logistic performance of the total system. In this manner it is furthermore possible to consider separately resource classes or order classes. The degree of logistic objective achievement for the total system e_{total} is accordingly determined by:

$$e_{\text{total}} = \frac{\sum_{i=1}^{n} \chi_i \cdot e_{\text{obj}}}{\sum_{i=1}^{n} \chi_i} \qquad (4.4)$$

with n as the number of all logistic objects within the system and χ as weighting factor of the logistic object. Through this calculation the degree of logistic objective achievement for production system is ascertainable.

4.2.5   Shop floor scenario

In the following the hypothesis made at the beginning will be verified through simulation studies. In a first step the achievement of logistic objectives, using the example of throughput time, at increasing structural static internal complexity for different autonomous control methods is in-

vestigated. For this purpose the previously introduced vectorial approach is implemented with the following weighting vector:

$$
\gamma = \begin{bmatrix} \gamma_{\text{Due date reliability}} \\ \gamma_{\text{Throughput time}} \\ \gamma_{\text{Utilization}} \\ \gamma_{\text{Work in process}} \end{bmatrix} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} \tag{4.5}
$$

To analyse the ability of an autonomous control to cope with rising complexity a simulation scenario is needed that allows to model different but comparable degrees of complexity and allows for the application of autonomous control methods. Furthermore it should be general enough to be valid for different classes of shop floor types. For these reasons a shop floor model in matrix format has been chosen, see figure 4.5. Subsequent productions steps are modelled horizontally while parallel stations are able to perform resembling processing steps.

At the source the raw materials for each product enter the system. Each product class has a different process plan i.e. a list of operations that have to be fulfilled on the related machine. In case of overload the part can decide autonomously to change the plan and to use a parallel machine instead. The final products leave the system via a drain.
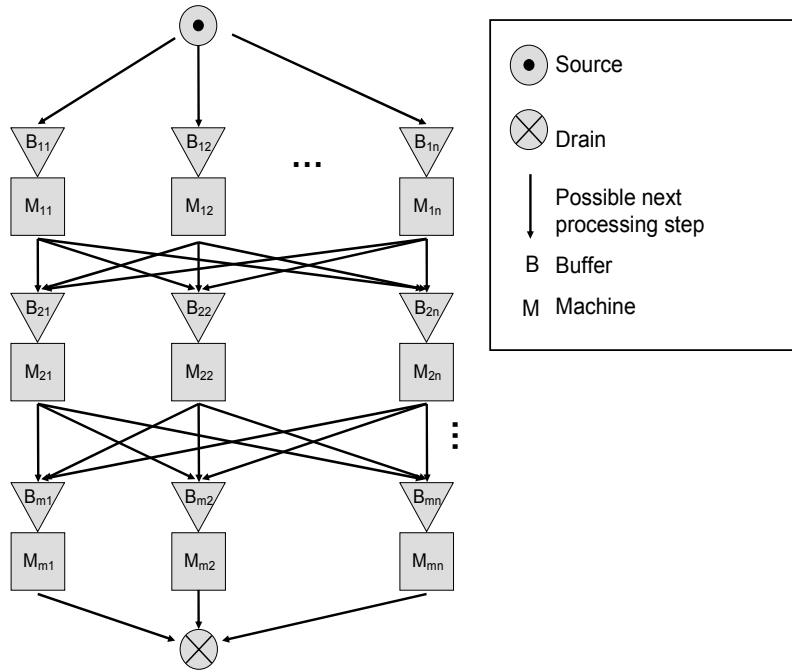
Fig. 4.6 Matrix model of a shop floor.

Autonomous control methods

Two different control methods will be compared. The first method compares the actual buffer states at all the parallel machines that are able to perform the next production steps. Therefore the buffer content is not counted in number of parts but in estimated processing time and the current buffer levels are calculated as the sum of the estimated processing time on the respective machine. When a part has to render the decision about its next processing step it compares the current buffer levels i.e. the estimated waiting time until processing and chooses the buffer with the shortest waiting time. This method will be called "queue length estimator" (QL).

The second method uses data from past events. Every time a processing step is accomplished and a part leaves a machine, the parts generate information's about the duration of processing and waiting time at the respective machine. The following parts use these data about past events to render the decision about the next production step. The parts compare the mean throughput times from parts of the same class and choose the ma-

chine with the lowest mean duration of waiting and processing. This method will be called "pheromone method" (PHE) as it is inspired by the behaviour of social insects which use pheromone trails to find shortest paths.

Simulation model

The ability to cope with rising complexity of these two methods for autonomous control will be analysed by varying two parameters of static structural internal complexity. On one hand, the size of the shop floor will be increased from 3x3 to 9x9 machines while the relative number of product/order classes will be kept constant i.e. the number of different products is equal to the number of parallel lines. On the other hand, the size of the shop floor will be held constant at 4x4 and the number of different product classes will be varied from 4 to 8 different products. The processing plans of the products differ i.e. it depends on the product class on which machines the product should be processed.
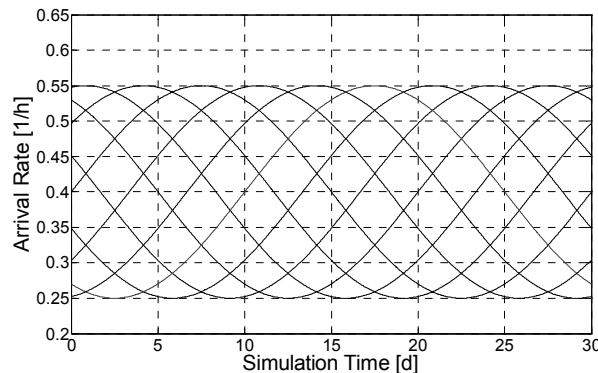

Fig. 4.7 Arrival rate during one simulation period for eight different products

To model a highly dynamic market situation the demand for the different products is set as an oscillating curve with situations of over and under load. The resulting arrival rates of parts that enter the shop floor are shown in figure 4.7.

As simulation period 30 days are chosen. After a phase of two month (with 30 days each) for avoiding transient effects the third month is used to measure the throughput times of every single part that is finished.

For balancing conditions the minimal processing time per manufacturing step is equally 2 hours. This minimal processing time can only be reached if the parts follow exactly the pre-planned processing plan without taking into account the current situation on the shop floor. If the parts decide to use parallel machines instead the throughput time will rise because of transport processes and set up times and higher processing times on parallel machines. This additional time depends on the number of parallel machines that are available for a production step. The additional time t_b is calculated by the distribution of one hour over the number of parallel machines:

$$t_b = {^{1h}}\!/\!_N \qquad\qquad (4.6)$$

Simulation results

For the simulation experiments a discrete event simulator is used. Figure 4.8 shows the influence of the rising network size on the mean throughput time of the whole orders. This time is measured as the time difference between job release i.e. the appearance of a part at the source and job completion i.e. leaving the shop floor at the drain. The figure shows the mean throughput time for all parts and all different product classes for the two different autonomous control methods. Additionally the minimal throughput time is shown which is a linear rising function of the network size because more production steps have to be undertaken as the shop floor size is increased. It appears that the rising system size has no effect on the mean throughput time applying the Queue Length Estimator as the curve is nearly parallel to the minimal throughput time. The Pheromome Method on the other hand shows a more and more worse performance as the mean

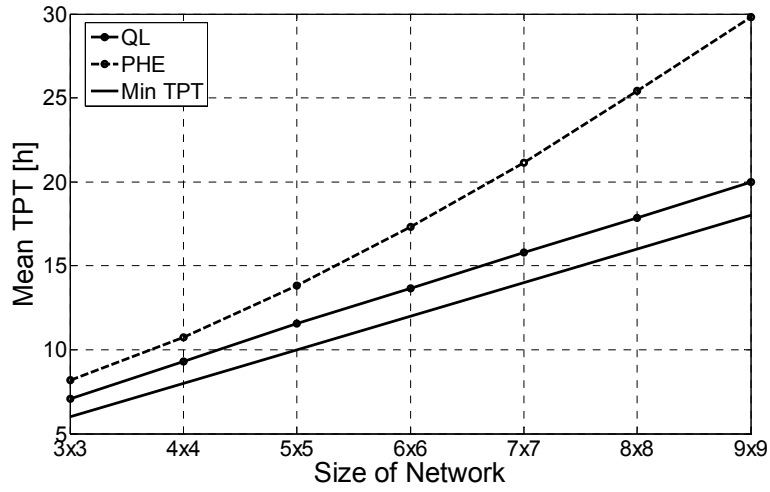throughput time rises exponentially with increasing network size.

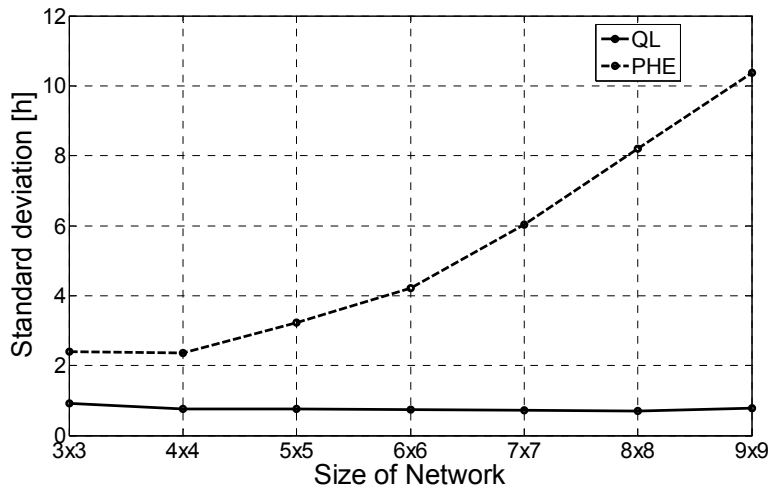
Fig. 4.8 Mean throughput time for different network sizes

Fig. 4.9 Standard deviation of the throughput time for different network sizes
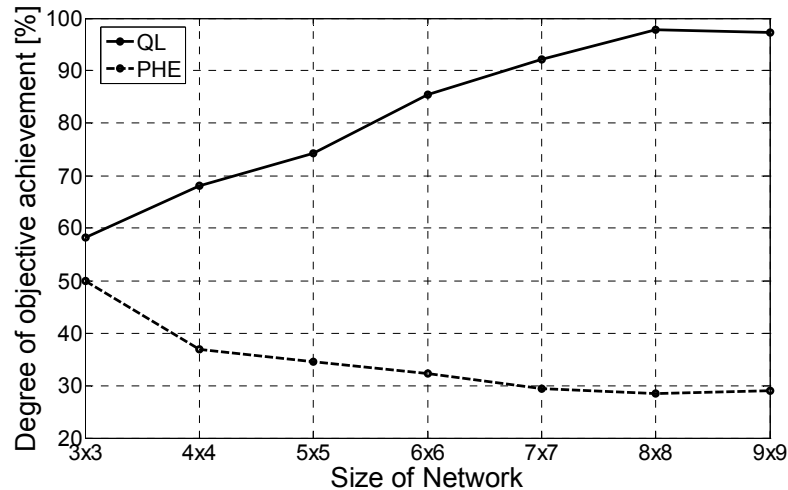
Fig. 4.10 Fraction of parts that are finished within 120% of the minimal through-put time for rising network size.

One realizes the same effect in the standard deviation of the throughput times which is displayed in figure 4.9. With rising network size the standard deviation is even decreasing for the QL method. For the PHE method also the standard deviation of the through put time is rising with higher network size.

The mean and the standard deviation are important measurements for the predictability of the throughput time and therefore essential for the due date reliability. Figure 4.10 shows the fraction of parts (called degree of job achievement) that are finished within 120% of the minimal throughput time. For the QL method this fraction rises with larger network size while for the PHE method this fraction decreases. This follows directly from the data for mean and variance. For the QL method mean and variance have a constant run. Therefore more and more parts are within the tolerance limit of 120% whose absolute value is rising analogue to the minimal through-put time. Accordingly the decreasing run of the curve for the PHE method follows from the data about mean and variance.
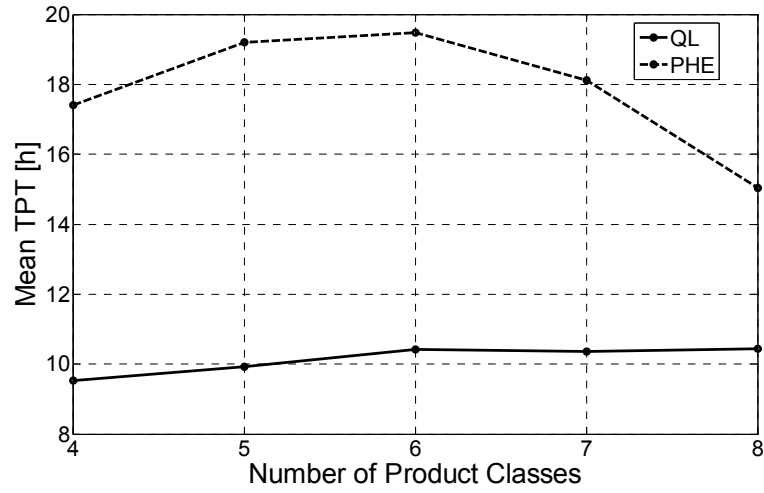
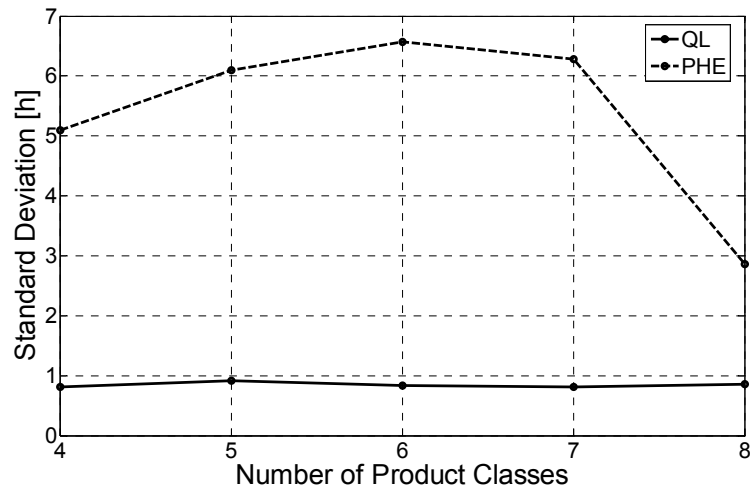**Fig. 4.11** Mean throughput time for different number of product classes

Fig. 4.12 Standard deviation of the throughput time for different number of product classes
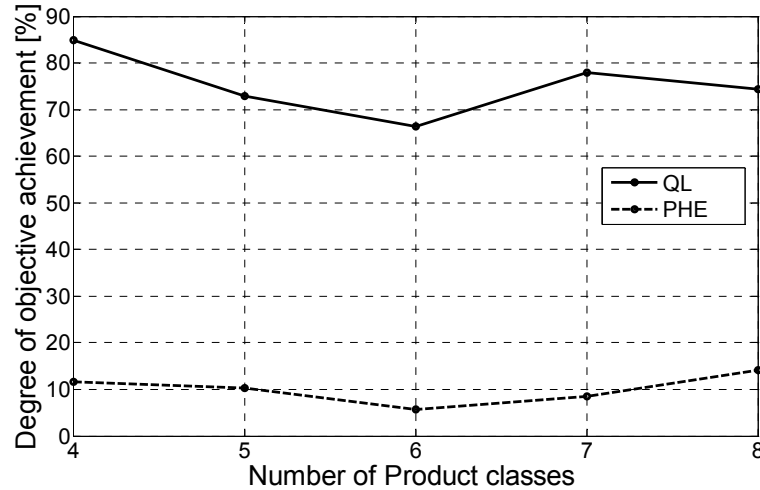
Fig. 4.13 Fraction of parts that are finalised within 120% of the minimal through-
put time for different number of product classes

In a second step the number of different product classes is varied. Figure
4.11 shows the mean throughput time within a 4x4 shop floor for four to
eight different products. Again the QL method shows a better performance
than the PHE method but a trend is observed that for a rising number of
product classes the performance of the PHE method is getting better. The
same effect can be seen in figure 4.12 where the standard deviation of the
throughput time is shown and for seven and eight product classes the PHE
method is showing a decreasing standard deviation. Figure 4.13 underlines
this effect in showing the fraction of parts that are finished within 120% of
the minimal throughput time and which are rising for the PHE method
from six to eight different products.

Interpretation

The appliance of the QL method shows a constant performance in face of
rising static structural internal complexity i.e. a higher number of machines
on the shop floor while the PHE method is not able to maintain a sufficient
performance. An exponential increase in mean and standard deviation of
the throughput times is observed. This is also caused by the fact that with a
rising number of machines the number of possible parallel machines is in-
creased and therefore the switching onto other less utilised machines is fa-
cilitated. Because the PHE method shows in general a slower behaviour
than the QL method the ability to switch more frequently is not exploited.

In the second case of a higher number of different order or product classes than parallel machines also the order arrival is modified. Because the mean utilization should be comparable the mean arrival rate has to be lowered every time a new product class is added to the model. Therefore the higher number of product classes causes also a more balanced utilisation of the system. This reduces the possibility and the necessity to change the processing plan and to move to a parallel machine. This improves the situation for the slower PHE method and allows for a trend to better results at a higher number of product classes.

The major difference between the two methods is the character of the used information. The QL method uses information about estimated processing times while the PHE method uses information about past events. Because the PHE method calculates a mean value of the past throughput times this method reacts more slowly on highly dynamic situations with fast changing system conditions. This causes fewer switches to parallel machines.

As a result one can state that in situations of a high number of machines that have to be equally utilised the QL method is more advisable because it shows a constant performance despite rising structural complexity.

The PHE method shows here a decreasing performance. In case of a high number of different products the PHE method could be an alternative. In particular when the trend is extrapolated the PHE method could show a better performance than the QL method.

4.2.6   Conclusions and outlook

At the beginning of this paper an assumption has been made that decentralised systems with autonomous control methods could be an approach to cope with rising complexity. A global definition as well as a definition in the context of engineering science was given. To verify in which cases the implementation of autonomous processes is of advantage in relation to conventionally managed processes an evaluation system is necessary. Main tasks regarding the development of this evaluation system are the operationalisation of the logistic objective achievement, the level of autonomy and the production systems complexity.

Within this article a vectorial approach to measure the achievement of logistic objectives together with a feedback loop for autonomous processes was introduced. By means of a complexity cube it is also possible to op-

erationalize the complexity of production systems regarding different types of complexity.

In simulation studies the ability to cope with rising complexity of two different autonomous control methods has been compared. Thereby different trends have been determined. The QL method based on a "look ahead approach" shows a constant performance at rising system complexity. It is obvious that systems of this size can also be controlled by traditional centralised PPC systems. But, if one extrapolates the trend there will be certainly a critical size were the constant performance of the QL method is superior to a centralized PPC method.

The PHE method based on a "look back approach" shows a slowly reacting behaviour and could be an alternative if it is not favourable to have permanent processing plan changes. So far the quality and dependability of data used by the two methods have not been taken into account. It seems to be realistic that information about past events are more reliable than information about future events. The smaller error in the information could further improve the performance of the QL method in comparison to the PHE method.

Further Research has to be done on the development of the evaluation system regarding the operationalization of the level of autonomous control and the definition of complexity parameters for the different vectors in the complexity cube. Furthermore additional simulation studies will help identifying for which types of increasing complexity the implementation of autonomously controlled processes is of advantage.

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