DYNAMICS OF DIRECT TRANSPORTS IN AUTONOMOUSLY CONTROLLED PRODUCTION NETWORKS

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ABSTRACT
Autonomous control of logistic processes opens up new potentials to improve the handling of internal and external dynamics in production networks. These networks are characterized by geographically dispersed coupled transport and production processes. This coupling may influence the dynamic behavior of the complete network, due to interdependencies between production and transport quantities and time scales. This paper addresses the impact of two direct transport strategies in an exemplarily production network scenario with autonomous controlled production plants. Relevant parameters of both transport strategies, which determine the transport quantity and the transport time scale, are varied in different simulation experiments in order to explore their impact of the dynamic behavior of the entire network and its elements.

Keywords: production networks, autonomous control, simulation, transportation mode

1. INTRODUCTION

Modern logistic systems are exposed to various dynamical changing parameters in their internal and external environment. Especially logistic networks, e.g. production networks or supply chains, are affected by dynamical changes (Sydow 2006, Wiendahl and Lutz 2002). These dynamics may be caused by an increasing desire of customers for individualized goods or the demand for short delivery times and a strict adherence to due dates. On the other hand, internal factors can cause unfavorable dynamic behavior of logistic networks itself, e.g. interdependencies between transportation and production processes. Especially, in production networks with geographically dispersed production facilities, which are sequentially involved in the production process, the (temporal) coordination of transport and production processes gets more and more important (Sauer 2006). In this regard, additional tasks and challenges for production planning and control (PPC) arise, like the assignment of orders to plants. Under these highly dynamic and complex conditions, current PPC methods cannot cope with disturbances or unforeseen events in an appropriate manner (Kim and Duffie 2004). The implementation of autonomous control is a promising approach to cope with increasing dynamics. This approach proposes decentralized coordination and decision-making of intelligent objects within a logistic system or network. It aims at improving the logistic performance due to flexible coping with dynamic complexity (Phillip et al. 2007). First approaches of autonomous control in production networks have been developed: these models have shown that autonomous control methods can improve the ability of a production network to handle dynamics, as well as the logistic performance of the network. Regarding the coupling of transport and production processes, these models revealed that complex interdependent dynamic effects can occur, which affect the logistic performance of the total system (Scholz-Reiter et al. 2009). Due to these coupled processes, the time scale of deliveries and transport quantities, as well as the logistic performance (measured in e.g. through put times, or work in process) of such networks are interrelated (Stadtler 2007). For example, a delivery according to a fixed transport schedule provides fixed delivery intervals, but the quantity depends on the production output of the previous production stages. Especially, the application of local autonomous control strategies requires knowledge about these interdependencies: autonomous control generates a more flexible and dynamic system behavior, which may lead to unfavorable dynamics in combination with a certain transport strategy.

Thus, this paper aims on investigating two different direct transport strategies: a fixed schedule strategy (FS) and a capacity based strategy (CS). These transport strategies are implemented in an autonomous controlled production network scenario. The model will be analyzed regarding varying transport quantities, varying time scales and the corresponding dynamic behavior of the network.

The paper is structured as follows: section 2 gives an overview about the concept of autonomous control in manufacturing. Section 3 focuses on production networks. The particular production network scenario will be presented in section 4. Section 4.1 describes the general structure of the network. Section 4.2 offers a description of the applied autonomous control methods. A detailed description of both direct transport strategies provides section 4.3. Subsequently, the simulation results are presented in section 5. Finally section 6 gives a summary and an outlook with further research directions.

2. AUTONOMOUS CONTROL IN MANUFACTURING

The collaborative research centre 637 'Autonomous cooperating Logistic Processes: A Paradigm Shift and its Limitations', which is founded by German research foundation, gives the following general definition of autonomous control: "Autonomous control describes processes of decentralized decision-making in heterarchical structures. It presumes interacting elements in non-deterministic systems, which possess the capability and possibility to render decisions independently. The objective of autonomous control is the achievement of increased robustness and positive emergence of the total system due to distributed and flexible coping with dynamics and complexity." (Windt and Hülsmann 2007). According to this definition, the main idea of autonomous cooperating logistic processes is a shift of decision-making capabilities form the total system to its elements. In the context of production systems, or production networks, intelligent logistic objects are allowed to route themselves through the logistic network according to their own objectives (Wiendahl and Lutz 2002). The term intelligent logistic object is comprehensively defined. It covers physical objects (e.g., machines, parts, etc.) as well as immaterial objects like production orders (Windt 2006, Philipp et al. 2007).

Recent work on autonomous controlled production systems showed that the application of autonomous control improves the logistic target achievement as well as the handling of internal and external disturbances (Scholz-Reiter et al. 2009b, Armbruster et al. 2006, Scholz-Reiter et al. 2005). As far as production networks are concerned, first approaches also provided promising results (Scholz-Reiter et al. 2007, Dashkovskiy et al. 2011). Scholz-Reiter et al. 2009 modeled a transport dispatching rule with fixed time intervals. It was shown that increasing inter transport times (ITT) may cause sudden changes in the total system performance and lead to an unpredictable system behavior. In order to analyze these dynamic effects, this paper focuses on two transport strategies in a similar scenario. It aims on evaluation of these strategies and on identifying relevant dynamic effects. The next section gives a brief overview about production networks in general.

3. PRODUCTION NETWORKS

Production networks are company or cross-company owned networks of geographically dispersed production facilities. Production networks focus on the mutual use of common resources and integrated planning of value adding processes in the network (Wiendahl and Lutz 2002). On the one hand this allows the achievement of economies of scale through the joint planning and use of production resources. On the other hand, these types of networks may react fast on internal or external disturbances due to redundancies of resources.

An integrated view on production planning and control and transports generates additional tasks: companies have to generate concepts for identifying new network partners, for the network design and for adjusting the PPC according to the network's purpose (Sydow 2006). The interconnection of production facilities opens up potentials of dealing flexible with disturbances. However, this creates complex interdependencies between production planning and control of plants and coordination of transports, e.g. decisions about assigning parts to plants or planning of transports and transport capacity (Sauer 2006, Alvarez 2007). There are first approaches aiming at optimization of combined production and transport processes (Erengüc et al. 1999). Due to the high degree of structural complexity of these problems, a complete optimization of large problem instances seems to be difficult. Thus, in this paper direct transport connections between plants are assumed. Direct shipping describes transport processes, which connect two locations directly, without any kind of transhipments (Gudehus 2005). Literature provides several optimisation approaches concerning transport frequency, transport costs and inventory costs of senders and recipients (e.g., Bertazzi and Speranza 2005, Wagner 2006).

This paper adapts a fixed schedule based and a capacity based direct transport strategy for initiating transports between two plants (Gudehus 2005). It focuses rather on the dynamic implications of these strategies on the networks performance than on the concrete optimisation.

4. PRODUCTION NETWORK SCENARIO

A scalable production network scenario with *jxk* different production locations is considered. This network comprises *j* different stages and *k* production plants per stage. Furthermore each plant in this scenario contains a shop floor with *n* parallel machines which are collocated on *m* different stages. Figure 1 depicts this scenario.

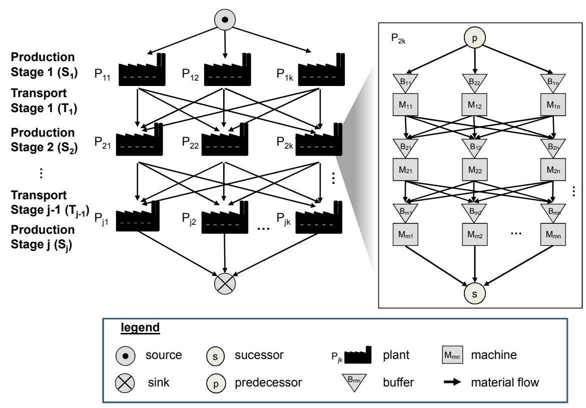

Figure 1: Production network scenario with *jxk* plants and *mxn* machines per plant

Each plant of a certain stage is connected to all plants on the succeeding stages via transport routes (see Figure 1). To analyze the impact of different direct transport strategies on the performance of an autonomous controlled network, a discrete event simulation model of a concrete scenario was build (similar to Scholz-Reiter et al. 2009). The following sections describe the parameterization of this scenario regarding: network structure, plant configuration and transport configuration.

4.1. Network structure

This scenario contains six different plants on four stages. On the first and on the last stage only one plant is located, which function as a source or sink, respectively. Stages two and three comprise two parallel plants each. The transport distances between all plants are set equally to 140 km and the speed of a truck is set to 70 km/h. Accordingly, transports between plants have a duration of 2 h. Table 1 summarizes the transport connections and distances for this scenario.

Table 1: distance matrix [km]

from / to	P_1	P_2	P_3	P_4	P_5	P_6
P_1	-	140	140	-	-	-
P_2	-	-	-	140	140	-
P_3	-	-	-	140	140	-
P_4	-	-	-	-	-	140
P_5	-	-	-	-	-	140

The considered network is able to process three different job types (Type A, Type B and Type C). All jobs arrive at plant P_1 and have to pass all stages of the network up to plant P_6. To model demand fluctuation, the arrival rate of parts is set as sine function (1). This function has a phase shift φ of 1/3 of a period for each job type, so that the maximal arrival rates of all job types do no cumulate.

$$\lambda(t) = \lambda_m + \alpha \cdot \sin(t + \varphi) \tag{1}$$

The mean arrival rate λ_m is set to 0.4 1/h. Due to this mean arrival rate in average every 2.5 h a part arrives. The amplitude α determines the intensity of the arrival rate fluctuation. It is set to α=0.2 1/h which causes variations of the inter-arrival time between 1.5 h and 3 h.

4.2. Plant configuration

Every plant in this scenario comprises a shop floor with three production stages and three parallel machines and buffers on each stage. Parts have to pass all stages of a plant. There are different processing times for each job type on the parallel machines of a certain production stage. Table 2 summarises these processing times.

Table 2.: Processing times of all job types on different processing lines [h:mm]

Plant	P_1, P_6			P_2, P_3, P_4, P_5		
Line / Type	1	2	3	1	2	3
Type A	2:00	3:00	2:30	4:00	5:00	4:30
Type B	2:30	2:00	3:00	4:30	4:00	5:00
Type C	3:00	2:30	2:00	5:00	4:30	4:00

Two different autonomous control methods are implemented: the queue length estimator method (QLE) and the pheromone based method (PHE). Both methods enable decentralised autonomous decision-making of parts. Parts using the QLE method compare the buffer levels of each production line at a certain stage and calculate their actual workload. In order to reduce their own throughput time (TPT) parts choose the machine with the lowest workload (for a detailed description see Scholz-Reiter et al. 2005).

The second method (PHE) aims on reducing the TPT, as well. In contrast to the QLE method, this method is inspired by the process of ants marking possible routes to food sources with pheromone trails. After being processed, parts leave information about waiting and processing times at the machine as a kind of artificial pheromone. Following parts are able to detect this information and choose the machine with the lowest mean value of artificial pheromones. The natural evaporation of pheromones is emulated by taking the moving average of the last five parts (for a detailed description see Armbruster et al. 2006, Scholz-Reiter et al. 2007).

4.3. Direct shipping strategies

Two simple direct shipping strategies are implemented in this scenario: fixed schedule transport strategy (FS) and capacity based transport initiation (CS). The FS initiates transports from one plant to the next plant according to fixed schedules, i.e. fixed transport intervals (*TI*). In cases of constant production rates and demands the transported quantities can be easily calculated (Gudehus 2005). On the other hand, in cases of varying production output the transported quantity q depends on the production output in a certain time interval *TI*. Contrary the CS strategy initiates transports according to a predefined transport capacity. Here the transport starts, when the number of produced parts equals this capacity (*C*). The transport quantity is constant and inter-transport time between transports depends on the production rate. Figure 2 visualises exemplarily the connection between both transport strategies.

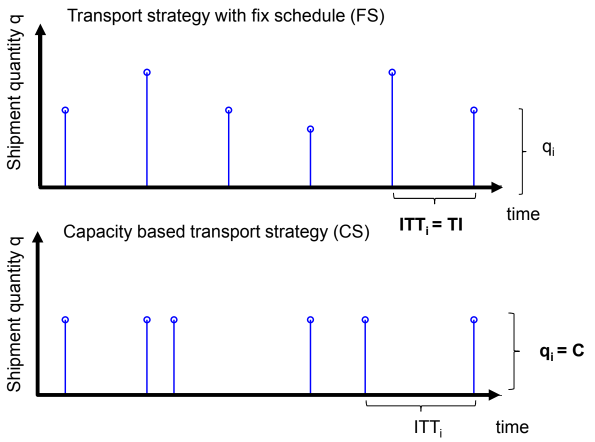

Figure 2: Shipment quantity and transport intervals of FS and CS

Figure 2 depicts two effects: the inter-transport times (*ITT*) for the FS are constant and equal to the predefined *TI*, but the shipment quantity may differ according to the production rate. In the CS, case the transport quantity q equals the predefined capacity C, but the *ITT* may vary between transports.

One can expect that both transport strategies affect the production network differently. In order to analyse the dynamic impact of both transport strategies, different simulation experiments are set up.

5. SIMULATION AND RESULTS

The analysis of the impact of transport strategies on the network dynamics is organised as follows: section 6.1 focuses on the connection between inter-transport times, transport quantities and the logistic performance of the entire network. The following section 6.2 gives a detailed analysis of the performance of the network stages.

5.1. Transport quantities and transport intervals

In order to investigate the influence of relevant parameters of both transport strategies (FS and CS) on the performance of the total network, several simulation runs are conducted with different configurations of *TI* and *C*. Figure 3 (a) depicts the quantities, which are transported along all transport connections of the network using the FS strategy. Each point in Figure 3 (a) represents the average of transported quantities $\bar{q}$ for a simulation run with a certain *TI* according to:

$$\bar{q}_{TI} = \frac{\sum q_i}{n}$$

Where $\bar{q}$ denotes the mean transport quantity per transport, q_i the quantity of the i^{th} transport and n the number of transports during the simulation period. The *TI* is increased in steps of 0.5 h per simulation run.

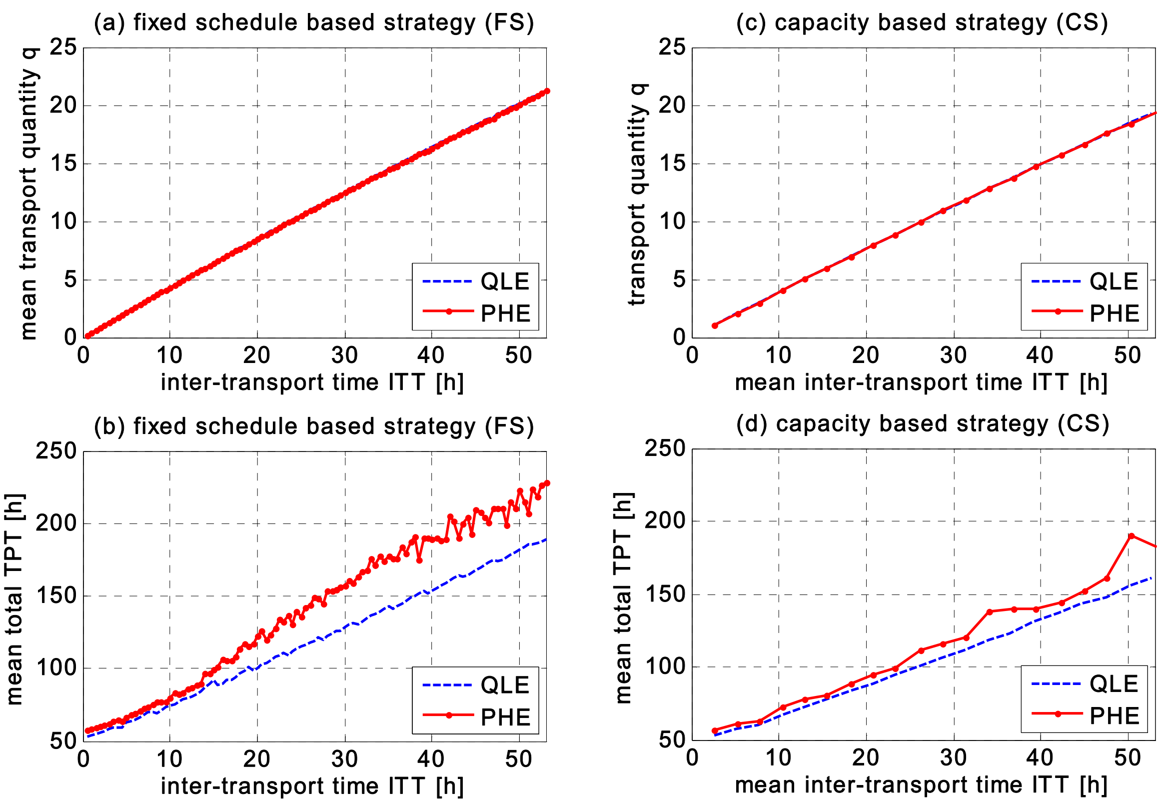

Figure 3: Mean transport quantities of FS against *ITT* (a), mean total TPT for FS against *ITT* (b), transport quantity of CS against mean *ITT* (c), mean TPT for CS against mean *ITT* (d)

Figure 3 (a) depicts a rising trend of transport quantities for an increasing *TI*. This can be explained by the production output of the pre-located plants, which sums up during the *TI*. Thus, transport quantity rises with the *TI*. Regarding the impact of the autonomous control strategies inside the plants on the mean transport quantity, one can notice, that the difference between both autonomous control methods in the mean transport quantities is very low. The curves for the QLE and the PHE methods overlap almost (Figure 3 (a)). Thus, it can be concluded that both methods do not affect the transported quantities in dependence of the *TI*. With regard to the performance of the entire network, Figure 3 (b) shows the mean total TPT for the corresponding *ITT*. In this context, the mean total TPT is measured as the mean time span that parts need to pass through the entire network. Comparing the mean TPT for the FS strategy and both autonomous control method in Figure 3 (b), one can find a significant difference between the QLE and the PHE method. The total TPT of PHE method is bigger for all *TI*. Especially higher *TI* values lead to a bigger difference of both methods. For the investigated range of *TI*, the average difference in total TPT between the QLE and the PHE method amounts 17.23%. In contrast to the average transport quantities, which seem to be independent from the autonomous control method, a correlation between the FS strategy and the autonomous control methods can be found here. It is assumed that both autonomous control methods have a different sensitiveness to a periodic transport interval *TI*. Especially the PHE method leads to a high total TPT in this case.

Contrary to the FS strategy, the CS strategy leads to transports with constant transport quantities and varying inter-transport times. Figure 3(c) and Figure 3(d) present the results of the CS. In particular Figure. 3 (c) depicts the average inter-transport times $\overline{ITT}$ for in dependence of increasing fixed transport quantities *C*:

$$\overline{ITT} = \frac{\sum ITT_i}{n}$$

Where ITT_i denotes the inter-transport times between transports, *C* the predefined quantity and *n* the amount of total transports. The quantity *C* is increased in steps of one piece per simulation run. To provide comparability to Figure 3 (a) the axis of dependent variable ($\overline{ITT_c}$) and the independent variable (*q*) are switched.

Figure 3 (c) shows that the impact of the QLE and the PHE method on the inter-transport times is low. Similar to Figure 3 (a) both curves are almost identical. Furthermore, Figure 3 (d) exposes that the total TPT for the CS in dependence of the corresponding mean $\overline{ITT}$. For the CS strategy, the QLE method performs better than the PHE method. In this case the relative difference between both methods is less than for the FS. However, it amounts 8.8% for the CS. This leads to the conclusion that the PHE method is more sensitive to fluctuation quantities arriving quantities (Figure 3 (b)) than to fixed quantities which have varying *ITT* (Figure 3 (d)). A similar conclusion can be drawn for the QLE method, but here the sensitiveness is less compared to the PHE method. In general, both local autonomous control methods perform better, if the CS strategy is applied.

5.2. Network performance

The results of the previous section showed, that this autonomous controlled network performs best using the CS strategy. This section investigates the impact of both transport strategies on the single stages of the network. For the further analysis, parallel located plants are seen as a production stage S_n and parallel transport connections as a transport stage T_n (see Figure 1). This allows a stagewise analysis of performance measures and a comparison of their changes on the different stages.

Figure 4 presents exemplarily the cumulated TPT of all network stages during a simulation period of 120 days. Each fraction in Figure 4 represent the TPT of parts in a production or a transport stage. Generally, Figure 4 contains simulation results of the PHE method for different *TI* values for the FS (*TI*=7 in Figure 4 (a), *TI*=50 in Figure 4 (b)) and *C* values for the CS (*C*=3 in Figure 4 (c), *C*=19 in Figure 4 (d)). These values of *TI* and *C* are exemplarily chosen in order to compare situations with small inter-transport times and big inter-transport times. Furthermore, these parameters lead to comparable mean inter-transport times and quantities according to Figure 3 (a) and Figure 3 (c).

Comparing Figure 4 (a) and Figure 4 (c), both strategies show a similar dynamic behaviour regarding the TPT. There are only small differences of TPT between both strategies per stage. The average difference is 1.44 h per stage. The situation with *TI*=50 and *C*=19 contrasts this. A difference between the dynamic behaviour in Figure 4 (c) and Figure 4 (d) can be clearly seen. Indeed the TPT through all stages is in average 21.12 % higher for the FS compared to the CS. Particularly the performance of the last production stage differs for both transport strategies. In the CS situation the mean TPT of the last stage is 36.46 h lower than in the FS situation. On this stage, there is only one plant which consolidates the material flow of the previous stages. It can be assumed that due to this consolidation dynamic fluctuation of previous stages in TPT sum up on this last stage and change the performance dramatically. Additionally, the FS strategy seems to amplify this effect. The highest mean TPT is recorded for this strategy. In contrast to this, the CS strategy reacts different. The maximum mean TPT can be found on the production stage S_3, followed by the mean TPT of production stage S_4. This implies that in the CS situation the effect of dynamic fluctuation summation is distributed on the last two stages. Table 3 confirms this. It presents the mean TPT and the standard deviation of the TPT for all stages of the network for both autonomous control methods and both transport strategies. It presents furthermore the mean total TPT (tTPT) and the total standard deviation (std) of the production network.

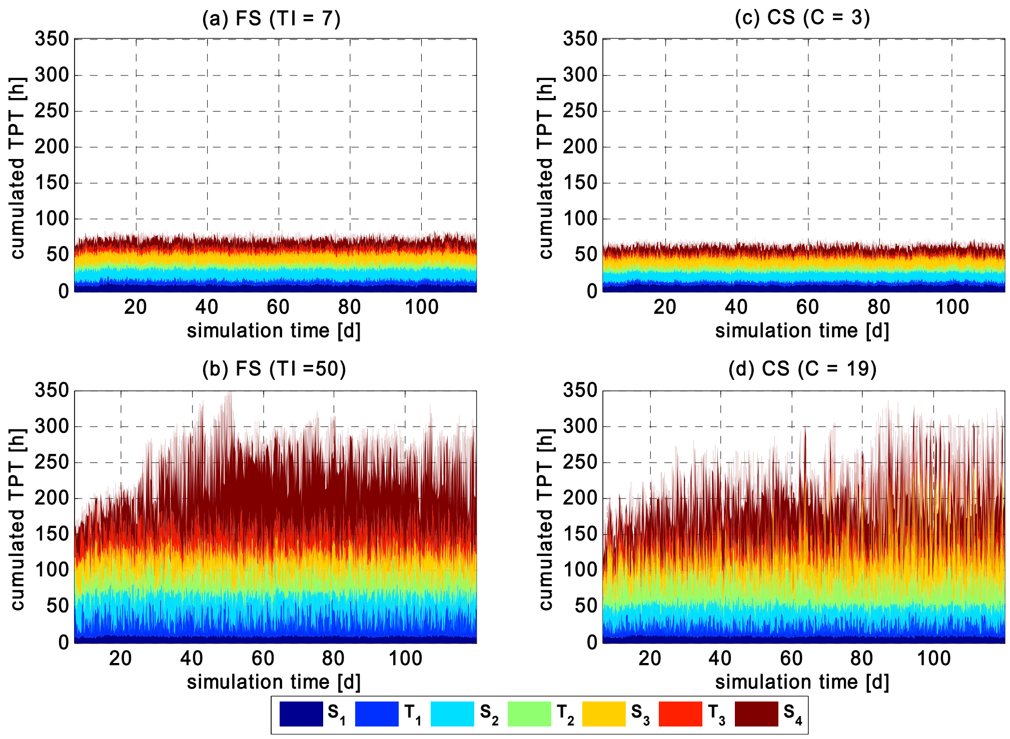

Figure 4: Cumulated TPT of all network stages for PHE against simulation time for FS and CS strategies: FS *TI*=7h (a), CS with *C*=3(b), FS with *TI*=50h (c), CS with *C*=19 (d)

For the FS situation, the standard deviation of all production location, except for S_4, are similar, but the biggest value can be found on the last stage (see Table 3). In contrast to this, the maximum values of the standard deviation can be found on S_3 and S_4.
Furthermore, Table 3 presents the results of simulation runs with the QLE method and both transport strategies. Generally, the performance of the QLE method follows a similar trend concerning the impact of both transport strategies. The QLE method performs best in case of the application of the CS. In contrast to the PHE method, the effect of converging material flows on the last production stage is much lower. Especially the results of the QLE method in combination with the FS with a transport interval of 50 h clarify that. The mean TPT of the last production stage is almost equal to every other network stages. The incoming workload can be processed better compared to the PHE method. Thus waiting and processing times in the last stage are lower.

Summarising these results concerning the logistic performance of single network stages, one can say, that the choice of the transport strategy influences the dynamic behaviour of the total network. The selected network scenario performs generally better using the CS strategy.

Table 3: Mean TPT and standard deviation of TPT of all network stages for all autonomous control methods (ACM) and transport strategies

Strategy	FS	FS	FS	FS	CS	CS	CS	CS
Parameter	*TI=7*	*TI=50*	*TI=7*	*TI=50*	*C=3*	*C=19*	*C=3*	*C=19*
ACM	QLE	QLE	PHE	PHE	QLE	QLE	PHE	PHE
avg. Q [p]	3.03	20.12	3.03	20.08	3	19	3	19
avg. ITT [h]	7	50	7	50	7.67	50.17	7.68	50.2
TPT S1 [h]	7.44	7.45	9.21	9.23	7.45	7.46	9.21	9.23
TPT T1 [h]	6.83	28.34	6.88	28.35	4.99	18.34	5.00	18.38
TPT S2 [h]	14.82	30.55	15.58	30.79	13.14	23.25	13.25	24.56
TPT T2 [h]	6.80	26.02	6.87	25.95	6.32	31.81	6.16	32.38
TPT S3 [h]	15.16	33.02	15.73	33.49	14.60	36.60	14.82	50.43
TPT T3 [h]	6.78	26.50	6.87	26.19	4.51	17.43	4.22	18.19
TPT S4 [h]	10.11	30.56	11.51	83.05	8.97	20.42	9.87	46.59
tTPT [h]	67.80	181.6	72.68	237.1	59.92	155.5	62.44	191.4
std S1 [h]	0.91	0.91	1.11	1.11	0.91	0.91	1.11	1.11
std T1 [h]	2.03	14.41	2.02	14.38	1.44	9.17	1.46	9.16
std S2 [h]	2.05	12.25	2.09	12.49	1.21	7.88	1.06	8.71
std T2 [h]	1.92	13.55	1.90	13.55	2.65	17.61	2.57	17.92
std S3 [h]	2.11	13.00	2.14	12.47	2.19	15.77	2.08	35.07
std T3 [h]	1.95	14.33	1.91	14.27	1.23	9.63	0.99	9.67
std S4 [h]	2.22	14.24	2.37	39.78	1.57	7.99	1.67	17.34
tstd [h]	3.56	18.49	4.34	46.04	3.85	22.26	3.91	25.64

6. SUMMARY AND OUTLOOK

A simulation model of an autonomous controlled production network scenario was introduced. It was shown that the transport performance, i.e. the inter-transport times and the transported quantities, of both strategies can be adjusted by varying the relevant parameters, i.e. transport interval and transport capacity. Furthermore it was shown that the logistic performance of the total network differs between both strategies, although the transport performance is equal. A deeper comparison of the performance of the single network stages revealed that the PHE method handles the incoming converging material flow on the last production stage better in the case of applying the CS strategy. In combination with the QLE method both transport strategies harmonise the material flow more, compared to the PHE method. In particular the QLE method performs superior in combination with the CS.
Basically, this paper presented that interdependencies between transport and production processes can not be neglected in the design of autonomous controlled production networks. Thus, further research will focus on the design of autonomous control methods, which take these dynamical aspects into account. Additionally, design of autonomous control methods which enable an autonomous assignment of parts to plants seems to be promising. On the other hand investigations of intelligent buffering policies, which allow to damp dynamic variations, are possible fields of future research activities.

ACKNOWLEDGMENTS
This research is funded by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes: A Paradigm Shift and its Limitations"

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