MODELING AND ANALYZING INTEGRATED AUTONOMOUSLY CONTROLLED PRODUCTION AND TRANSPORT PROCESSES

B. Scholz-Reiter, M. Görges, T. Jagalski
Department of production planning and control, University of Bremen, Hochschulring 20, Bremen, Germany

Abstract
The efficient coordination of production and transport processes in large scale logistic networks is a challenging task. In respect of structural complexity most of the network related planning problems are NP-hard. Accordingly, optimal solutions can hardly be found. Moreover, these networks are exposed to dynamically changing factors, which additionally exacerbate planning and control of the logistic processes. In this context decentralized control approaches support the planning and coordination of network spanning logistic processes. This paper presents two decentralized autonomous control approaches, which address integrated transport and production processes. These approaches are evaluated in different simulation experiments in an exemplarily production network scenario. It will be shown that both autonomous control methods are suitable for different dynamic situations.

Keywords:
Autonomous control, Production networks, Simulation

1 INTRODUCTION

Production networks are networks of company or cross company owned facilities, which aim at an integrated planning of geographically dispersed logistic processes and the usage of common resources [1]. In production networks with geographical dispersed production plants, additional tasks for production planning and control (PPC) arise, e.g. the assignment of jobs to plants or the planning of transports. Thus, the coordination of transport and production processes gets more and more important [2, 3]. Conventional incremental planning and control methods have shortcomings to cope with these additional tasks [4]. The implementation of decentralized approaches, e.g. autonomous control, is a promising solution for this problem [1, 5, 6]. Decentralized autonomous control intents to improve the performance of a logistic system by a distributed and flexible coping with complexity. According to this concept, single jobs are able to make and execute routing decisions on their own [7]. The implementation of autonomous control methods can help to improve the logistics performance and the robustness of production systems [8, 9]. One can assume that an integrated autonomous control of both, production and transport processes increases the logistic performance of production networks [10]. Thus, this paper focuses on integrated autonomously controlled production and transport logistic processes. It presents two methods, which enable autonomous decision making on the network layer, in terms of an autonomous allocation of parts to plants. Subsequently, it investigates the dynamic interplay between existing autonomous control methods for the production layer and the network layer. This is crucial due to the fact that the efficiency of different autonomous control methods depends on scenario specific parameters [11]. This paper will show that the network related autonomous control methods have different operating points. Therefore, an exemplarily production network scenario is considered. Both autonomous control methods are evaluated in this scenario, regarding varying degrees of external dynamics. It will be shown that both methods are suitable for different dynamic situations.

This paper is organized as follows: Section 2 presents the theoretical concept of autonomous control. The scenario description is given in section 3. Subsequently, section 4 presents the modeling of the network related autonomous control methods. In section 5 the simulation results are presented and discussed. Finally, section 6 summarizes the results and gives an outlook.

2 AUTONOMOUS CONTROL

The collaborative research centre 637 “Autonomous cooperating Logistic Processes: A Paradigm Shift and its Limitations”, which is founded by the 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.“ [12]. According to this definition, the main idea of autonomously controlled logistic processes is a shift of decision making capabilities from the total system to the single system elements. These autonomous acting elements, i.e. intelligent logistic objects, are able to gather information about local system states and to make and execute decisions locally based on this information. The term intelligent logistic object covers physical objects (e.g., machines, parts, etc.), as well as immaterial objects like production orders [7].

In the context of production logistics the application of autonomous control methods has already shown promising results (cf. [8, 9, 13]). However, comparative studies showed that the applicability of different autonomous control methods depends mainly on the certain scenario and on the corresponding logistic targets [11]. Literature provides several autonomous control approaches, which are based on different decision logics [8, 9]. Wind et al. 2009 [14] give a classification in three categories: rational, bounded rational and combined strategies. One group of the bounded rational strategies are bio-analogue strategies, which are inspired by biological processes, e.g. foraging behavior of bees or ants [15, 16]. On the other hand decisions based on rational strategies consider solely pure rational performance measures, for example estimated processing and waiting times [8].

As far as production networks are concerned, different autonomous control approaches were already formulated. Similar to single production systems autonomous control leads to promising results (e.g., [10]). Nevertheless, these

Table 1: Scenario configuration – processing times [h:mm]

Processing time parameter	$P^{1,1}_{m,o}$, $P^{4,1}_{m,o}$			$P^{2,1}_{m,o}$, $P^{3,1}_{m,o}$			$P^{2,2}_{m,o}$, $P^{3,2}_{m,o}$		
Type (o) \ Line (m)	1	2	3	1	2	3	1	2	3
Type A	2:00	3:00	2:30	3:00	4:00	3:30	5:00	6:00	5:30
Type B	2:30	2:00	3:00	3:30	3:00	4:00	5:30	5:00	6:00
Type C	3:00	2:30	2:00	4:00	3:30	3:00	6:00	5:30	5:00

studies focused on interconnected autonomously controlled plants. It is assumed that additional autonomous control on the network level may open new potentials of the logistic performance.

3 SCENARIO

A matrix-like production network scenario is considered (similar to [10]). It consists of a set of production plants, which are connected via transport routes. Additionally, each plant comprises a shop-floor, which is organized in a matrix-like shape, as well. Figure 1 depicts this general structure.

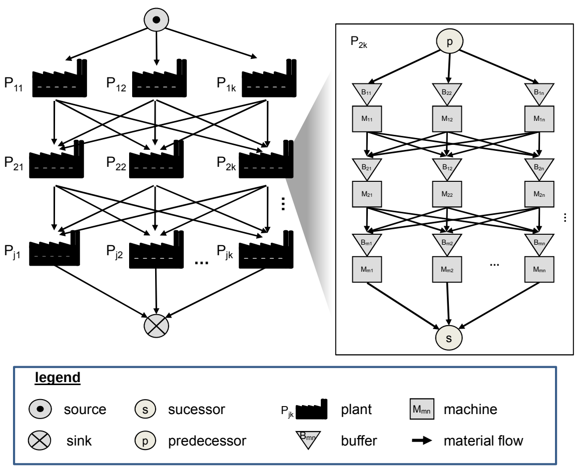

Figure 1: General production network scenario [10]

In order to model the logistic processes in this scenario a set of variables is defined. All parameters can be formalized as flows:

Parameter

J	Number of jobs (index j)
O	Number of job types (Index o)
S	Number of network stages (index s)
F^{s}	Number of parallel plants on network stage s (index f and l)
$T^{s,f}$	Number of production stages in plant f on network stage s (index t)
$M^{s,f}_{t}$	Number of parallel machines in plant f on network stage s on production stage t (index m)
$P^{s,f}_{t,m,o}$	processing time of job type o on machine m on production stage t in plant k on network stage s
O	Number of job types (Index o)
v	velocity of a truck
q	capacity of trucks
$D^{s+1,l}_{s,f}$	distance between plant f on network stage s and plant l on network stage $s+1$

Variables

$WIP^{s+1,l}_{s,f}$	Work in progress transported from plant k on stage s to Plant j on stage $s+1$
$WIP^{s,f}$	Work in progress in plant k on stage s
$C^{s,f}_{j}$	Completion time of job j in Plant k on network stage s
$r^{s,f}_{j,o}$	release time of job j in Plant k on network stage s
$TPT^{s,f}_{j}$	throughput time of job j in Plant k on network stage s : $TPT^{s,k}_{j} = C^{s,k}_{j} - r^{s,k}_{j}$
$TTPT_{j}$	throughput time of job j through the entire network
$TT^{s+1,l}_{j,s,f}$	transportation time of job j from plant f on stage s to plant on stage $s+1$: $TT^{s+1,l}_{j,s,f} = r^{s+1,l}_{j,o} - C^{s,f}_{j}$

For the purpose of the evaluation a particular configuration of this general scenario is modelled:

The scenario comprises six different plants on four network stages, similar to [10]. On stage one and on stage four there is only one plant. On stage two and three there are two collocated plants. Additionally, every plant consists of a shop floor with three parallel production lines and three machines per production line. Figure 1 shows the general structure of the scenario.

There are three different job types in this scenario (*O=3*). These job types differ in their processing times on the shop floor level. The processing times are set as summarised in Table 1.

The jobs arrive in plant 1 at stage 1 with a certain arrival rate. In order to model a dynamic seasonal demand, this arrival rate *u(t)* is set to a sine function (1):

$$u(t) = \lambda + \alpha \cdot \sin(t + \varphi) \qquad (1)$$

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. The variable λ defines the mean of the arrival rate and is set to λ=0.4 1/h in all simulation runs. The second variable α determines the intensity of the arrival rate fluctuation. This factor is varied systematically in order to generate different dynamic situations. It is stepwise increased in the interval [0, 0.2]. As a consequence the release date $r^{1,1}_{j,o}$ of a job *j* in plant 1 is set to the arrival rate function *u(t)*.

Transports between plants are triggered by a “go when full policy” (as described in [17]). This means, that a transport from on plant to the next plant starts, when a predefined quantity of parts is finished in one plant. This quantity is set according to the capacity of the trucks. Such a transportation policy is commonly used in door to door transports [17]. For this scenario the truck capacity is set to *q=5* parts. The distances between the plants $D_{s,f}^{s+1,l}$ are depicted in Table 2. The velocity of all trucks is set *to v=70* km/h. Hence, a transport from one plant to the next takes 2 hours.

Table 2: Distance matrix [km]

	to					
from	plant[11]	plant[21]	plant[22]	plant[31]	plant[32]	plant[41]
plant[11]	-	140	140			
plant[21]		-		140	140	
plant[22]			-	140	140	
plant[31]				-		140
plant[32]					-	140
plant[41]						-

Parts in this scenario are able to decide about routes on the network and on the shop floor level autonomously. These methods are presented in the following.

4 AUTONOMOUS CONTROL METHODS

Section 4.1 and 4.2 present the applied autonomous control methods for the shop floor level. On the basis of these methods, section 4.3 and 4.4 present adopted versions of these methods for autonomous decision making on the network level.

4.1 Queue length estimator for production

In former work an autonomous control method was introduced, which enacts parts in a production system to make an autonomous assignment to production resources, i.e. machines [8]. Parts in the production are able to interact with others and to gather information about the current workload. Similar to the join the shortest queue policy (Foley and McDonald 2001) the part collect information about the amount of waiting parts in the relevant buffers. Additionally the parts calculate the estimated waiting time for each alternative. Extensive investigation of this queue length estimator (QLE) method in various production scenarios showed that it improves the systems handling of dynamic disturbances [9]. This method is named QLE^p in the following. It aims at reducing the throughput times of parts in a production plant.

4.2 Pheromone based method for production

A pheromone based approach (PHE) is presented in [15]. This approach is based on the idea to imitate the process of ants marking possible routes to food sources. Ants leave pheromone marks between the nest and food sources. Other ants can detect those pheromones and will follow the tail with the highest concentration of pheromones [19, 20]. This is transferred to production scenarios: During the production process parts leave information about their processing and waiting times at a corresponding machine. Following parts entering a stage of the shop floor compare this artificial pheromone concentration by computing average value of the waiting time data of the last five parts and choose a production line. The application of a moving average is an approximation to natural process. Thus, the pheromone concentration depends on waiting and processing times of previous jobs. This method is named PHE^p in the following. Similar to the QLE^p this method aims at reducing the throughput times of parts through the production facility.

4.3 Queue length estimator for networks

To enable autonomous assignment decisions of parts to plants on the network level, the QLE^p method is transferred to a new method called QLE^n. The QLE^n method collects information about the next network stage. It estimates the duration of the transport, waiting and processing times in the subsequent plants (see equation 2). Therefore, a part compares the amount of traveling parts from one plant to the succeeding plant ($WIP_{s,k}^{s+1,l}$) multiplied by the minimal processing times in the subsequent plant on the first production stage ($p_{1,u}^{s+1,l}$) as an estimation of the waiting time in the next plant. The second term takes the transport duration for the distance $D_{s,k}^{s+1,l}$ and the truck velocity *v* into account.

$$Q_{s,f}^{s+1,l} = \frac{WIP_{s,f}^{s+1,l} \cdot \min_u(p_{1,u}^{s+1,l})}{M_1^{s+1,l}} + \frac{D_{s,k}^{s+1,l}}{v} \tag{2}$$

A part calculates the $Q_{s,k}^{s+1,l}$ values of all succeeding plants and chooses the plant with the lowest value for further processing. By doing this, the part *j* tries to minimize its total throughput time (*TTPT$_j$*), which is the time spend by a part to pass the entire production network.

4.4 Pheromone based method for networks

Similar to the PHE^p method, the PHE^n method uses information of past events for decision making. Intelligent parts choose one of the alternative succeeding plants according to information about the throughput times of previous parts. In contrast to the PHE^p method this information is not limited to the waiting times at the next machine. It focuses further on the necessary time to pass the transport system and the corresponding plant. This waiting time is denoted as $W_{o,j}^{s,k}$, where *j* is the index of the *jth* job which passed the plant *k* on stage *s*. Each plant has a vector $\vec{W}_o^{s,k}$, where *O* represents the job type.

Whenever a part *j* leaves a plant the waiting time for transports and the processing time of this part are inserted into the corresponding $W_{o,j}^{s,k}$. Equation 3 shows this. The value $W_{o,i}^{s,k}$ of the last part *i* is inserted at the first position of the vector $\vec{W}_o^{s,k}$.

$$\overline{W}_o^{s,k} = \begin{pmatrix} W_{o,i+1}^{sk} \\ W_{o,i}^{sk} \\ \vdots \\ W_{o,1}^{sk} \end{pmatrix} \tag{3}$$

After being processed in one plant the part has to choose a succeeding plant. Therefore, the PHE^n method calculates a moving average over the last *L* parts as an artificial pheromone (4). Similar to the PHE^p method the moving average is used to emulate the evaporation of natural pheromones.

$$PHE_{s,k} = \frac{\sum_{i=1}^{L} W_{o,i}^{sk}}{L} \tag{4}$$

After calculating the concentration of artificial pheromones, the part chooses the succeeding plant with the lowest average transportation and processing times.

Like the QLE^n, the PHE^n method aims at reducing the total throughput time of a job *j* (*TTPTj*).

5 SIMULATION RESULTS

In order to evaluate all possible combinations of shop-floor and network related autonomous control methods (i.e. QLE^n/QLE^p, QLE^n/PHE^p PHE^n/QLE^p and PHE^n/PHE^p), a set of simulation experiments is defined (Table 3). Section 5.1 presents the simulation results concerning the impact of *α* and presents different operating points of each combination. Note, that *α* determines the amplitude of the arrival function *u(t)*. This affect the dynamics of the system: For small values of *α* the arrival rate is nearly constant. An increase of *α* leads to oscillating variations in the incoming workload.

Table 3: Setup of simulation experiments

applied combination		arrival rate amplitude α				
network level	shop floor level	0.025	0.05	0.75	…	0.2
QLE^n	QLE^p					
QLE^n	PHE^p					
PHE^n	QLE^p					
PHE^n	PHE^p					

Subsequently, section 5.2 presents simulation results that focus on the underlying dynamic behavior of the total system as a reason of the identified operating points. Moreover, these simulation runs investigate the impact of the evaporation parameter *L* of the PHE^n method.

5.1 Impact of external dynamics

Figure 2 a) shows the general performance of the applied combinations of autonomous control methods, i.e. QLE^n/QLE^p, QLE^n/PHE^p PHE^n/QLE^p and PHE^n/PHE^p, in different dynamic situations. In order to generate different dynamics the amplitude of the arrival rate is varied systematically between *α=0.025* 1/h and *α=0.2* 1/h in steps of 0.025 1/h. Each point in Figure 2 a) represents the results of one simulation run. It depicts the mean value of the *TTPTj* for each combination. In order to provide comparability, Figure 2 b) presents the corresponding standard deviation. In total Figure 2 comprises data of 44 different simulation runs.

Regarding the results of the combination QLE^n/QLE^p an almost flat curve is observed. This combination leads for the range between *α=0.025* 1/h and *α=0.2 1/h* to nearly constant mean *TTPT* values, which are about 73.06 h. The maximal deviation can be found between *α=0.025* 1/h and *α=0.2 1/h*, which is 3.12%. The curve of the QLE^n/PHE^p combination is similar, but the absolute values differ. Here, the mean *TTPT* values are in average 5.9% higher compared to the combination QLE^n/QLE^p. In contrast to these results, the curves of the PHE^n method (PHE^n/QLE^p and PHE^n/PHE^p) differ from a qualitative and a quantitative perspective.

The parameter *L*, which determines the evaporation of the artificial pheromones, is kept constant in these simulation runs (*L=15*). In the case of the PHE^n/QLE^p combination, nearly constant results are obtained between *α=0.025* 1/h and *α=0.125 1/h*. Beyond this point the mean *TTPT* increases suddenly from 68.39 h to 77.78 h. Nevertheless, for values of *α≤0.125*, this combination leads to the best results concerning the mean *TTPT*. Beyond *α>0.125* the combination of QLE^n/QLE^p provides the best performance.

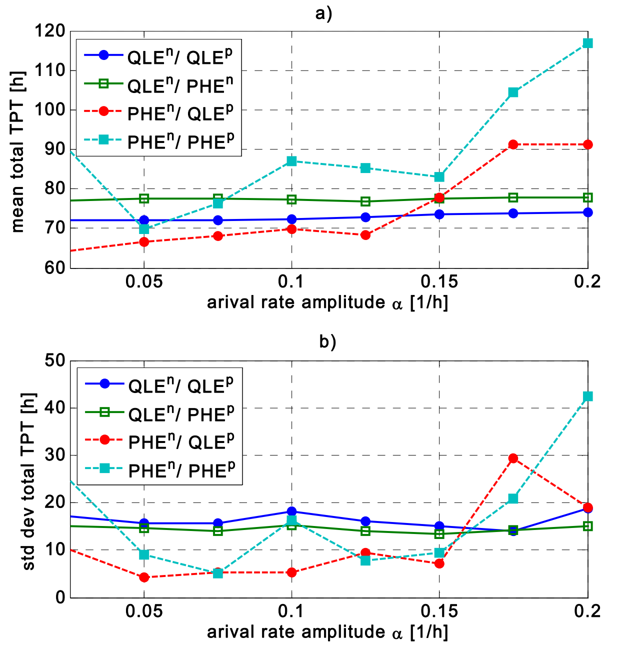

Figure2: a) Mean($TTPT_j$) against arrival rate amplitude (*α*); b) std dev ($TTPT_j$) against arrival rate amplitude (*α*)

The results for the PHE^n/PHE^p combination are not that straight forward. Figure 2 a) shows an increasing trend for this combination with rising values of *α*. In the less dynamic situation (*α=0.05*) this combination provides the second best results (*mean TTPT=69.85* h), but when increasing α the mean *TTPT* gets worse. It reaches its maximum for *α=0.2* with a mean *TTPT* of 116.82 h. This is a deviation of 36.66 % from the best mean *TTPT* found.

Summarising the results of these simulation runs, one can assume, that the combination of PHE^n/QLE^p is the best for less dynamic situations. While in a more dynamic environment (*α>0.125* 1/h) the QLE^n/QLE^p combination operates best in this scenario. In spite of that, the application of QLE^n/PHE^p seems to be not suitable for this scenario. It is outperformed by the QLE^n/QLE^p combination for every value of *α*.

In the next step the dynamic interplay between network and production related autonomous control methods is investigated, in order to identify the basic mechanisms, which lead to the obtained results. Subsequently, the impact of the evaporation constant *L* of the PHE^n method is investigated.

5.2 Dynamics of network and shop-floor related methods

Figure 3 presents exemplarily the $TTPT_j$ against the simulation time of four different simulation runs. Figure 3 a) and Figure 3 b) represent the results of the QLE^n/QLE^p combination in a less and in more dynamic situation (*α=0.025 1/h* and *α=0.15 1/h*). In the second row the graphs for the PHE^n/QLE^p combination are depicted (Figure 3 c and Figure 3 d). The results in Figure 3 give some indications concerning the systems behavior in both situations. Figure 3 a) and b) indicated that the impact of variations of *α* on the mean *TTPT* of the QLE^n/QLE^p is low. Similar to Figure 2, a step of the mean *TTPT* for the

PHE^n/QLE^p combination can be found in Figure 3c) and d). Moreover, the shapes of both curves differ significantly. For *α=0.05 1/h* the curve has an evenly pattern with a mean value of 67.7 h. In contrast to this, a nearly periodic pattern can be found in the situation of *α=0.15 1/h.* This curve has three comparable maxima, which occur periodically every 30 days.

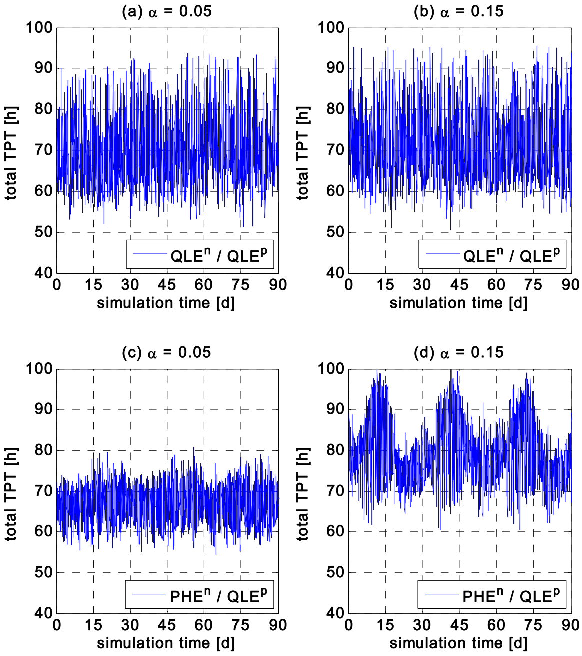

Figure 3: *TTPT$_j$* against simulation time

It is assumed, that one reason for the periodically behaviour of the PHE^n method is the choice of the evaporation constant *L*. In order to prove this, Figure 4 presents the *TTPT* curves of the PHE^n/QLE^p combination for different arbitrary chosen parameters of *L* (*L=2, L=40, L=80* and *L=100*) and *α=0.15 1/h.*

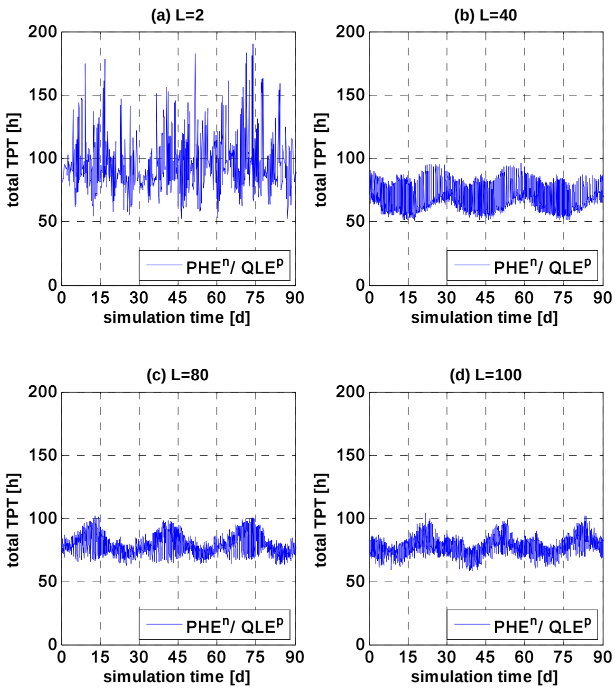

Figure 4: Total TPT against simulation time for *L=2* (a), *L=40* (b), *L=80* (c) and *L=100* (d)

Figure 4 confirms the impact of *L* on the total performance of the network. It shows, that the shape of the *TTPT* curves differ significantly for the chosen values of *L*. For *L=40*, *L=80* and *L=100* an alternating behaviour, similar to Figure 4 d) is observed. On the other hand, for *L=2* no periodicity in the *TTPT* curve appears. With regard to the mean *TTPT*, the choice of *L=40* leads to the best mean value (72.2 h), compared to *L=2* (90.81h), *L=80* (81.41h) and *L=100* (81.63h). It can be noticed, that this value for *L=40* is even lower than that of the QLE^n/QLE^p combination for (α=0.15). Figure 5 depicts the impact of *L* on the networks performance more detailed. It presents the simulation results concerning the mean *TTPT* for the scenario with *α=0.15 1/h* for increasing values of *L*.

These simulation results show that the mean *TTPT* depends on the chosen values of *L*. The variations identified in Figure 4 can be also found in Figure 5.

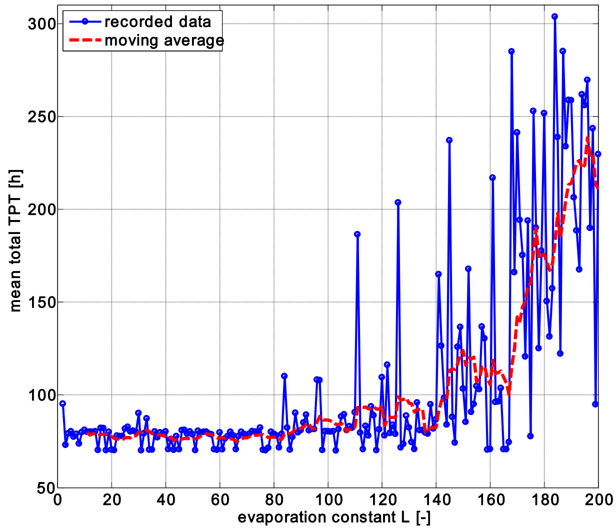

Figure 5: Mean *TTPT$_j$* against evaporation constant *L* for the QLE^n/PHE^p combination

For bigger evaporation constants (*L≥110*) there are stronger variations in the results. In order to provide a comprehensible understanding of the impact of the evaporation constant Figure 5 contains a moving average over the last 10 results. According to the moving average the variations for *L<110* are moderate. The results remain on the same level. However, an increasing trend can be recognized with increasing values of the evaporation constant form *L≥110.* A reason for this increasing trend is the actuality of the data used by the PHE^n method: The evaporation constant determines according to equation 4 the amount of data which is considered for calculating the concentration of artificial pheromones. The bigger the evaporation constant *L*, the more data form the past is used. Figure 5 indicates the time horizon, which is connected with the evaporation constant is too big for values above *L≥110.* In this case the data does not represent the actual system state in an appropriate manner. Hence, the autonomous assignment of parts to plants is suboptimal. This effect seems to continue with increasing values of the evaporation constant.

To sum up, one can summarize, that the parameter *L* of the PHE^n method has a crucial impact on the performance of the entire network. By choosing a suitable evaporation constant, the system can be adjusted according to the corresponding scenario parameters. In the case at hand the analysis showed a good performance for choosing *L=40.*

6 SUMMARY AND OUTLOOK

This paper presented a general model of a production network scenario. Based on this scenario, two new autonomous control methods were developed and described in detail. Subsequently, the logistic performance of both new methods was evaluated. This evaluation was based on the total throughput time (*TTPT*). It showed that both methods have different operation fields, when they are combined with already existing autonomous control methods for production logistics. The PHE^n method seems to be more suitable to less dynamic situations, while the QLE^n method performs better in more dynamic situations. Especially the combination of the PHE^n with the QLE^p method evinced the best performance in the less dynamic situation, while the combination QLE^n/QLE^p performs best in a more volatile environment. Furthermore the analysis focused on the effect of evaporation constant of the pheromone based approach. It identified the impact of this constant on the dynamic behaviour and on the performance of the total system. A critical value of this parameter was determined, exemplarily. The accuracy of data used by the PHE^n method seems to be not sufficient for autonomous decision making at this critical point. It was furthermore shown, that the systems behaviour of the total system is influenced by evaporation parameter below this point. Related to this, new topics for further investigations arise. Structural extensions of the network scenario, e.g. adding network and production stages or transport connections, are one of these. Additionally to this, in depth investigations of the impact of the evaporation parameter L of the PHE^n method are necessary.

ACKNOWLEDGEMENTS

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

7 REFERENCES

[1] Wiendahl, H.-P., Lutz, S., Production in Networks, Annals of the CIRP – Manufacturing Technology, 51 (2), 2002, 1–14.

[2] Sauer, J., Modeling and solving multi-site scheduling problems, Planning in Intelligent Systems: Aspects, Motivations and Method, Wiley, 2006.

[3] Erengünc, S. S., Simpson, N. C., Vakharia, A. J., Integrated production/distribution planning in supply chains, European Journal of Operational Research, 115 (2), 1999, 219–236.

[4] Ivanov D., An adaptive framework for aligning (re)planning decisions on supply chain strategy, design, tactics, and operations, International Journal of Production Research, 48(13), 2010, 3999-4017.

[5] Huang, G.Q., Lau, J.S.K, Mak, K.L., The impacts of sharing production information on supply chain dynamics: a review of the literature, International Journal of Production Research, 41(7), 2003, 1483-1517.

[6] Graves, S.C., Willems, S.P., Supply chain design: safety stock placement and supply chain configuration, Handbooks in operations research and management science, supply chain management: design, coordination and operation, Elsevier, 2003.

[7] Windt, K., Selbststeuerung intelligenter Objekte in der Logistik, Selbstorganisation – Ein Denksystem für Natur und Gesellschaft, Böhlau Verlag, Köln, 2006.

[8] Scholz-Reiter, B., Freitag, M., de Beer, C., Jagalski, T., Modelling and Analysis of Autonomous Shop Floor Control, In: Proc. of 38th CIRP International Seminar on Manufacturing Systems. Florianopolis, Brazil, 2005.

[9] Scholz-Reiter, B., Görges, M., Philipp, T., Autonomously controlled production systems-Influence of autonomous control level on logistic performance, CIRP Annals - Manufacturing Technology, 58(1), 2009, 395-398.

[10] Scholz-Reiter, B., Görges, M., Jagalski, T., Mehrsai, A., Modelling and Analysis of Autonomously Controlled Production Networks, Proceedings of the 13th IFAC Symposium on Information Control Problems in Manufacturing. Moscow, Russia, 2009, 850-855.

[11] Hülsmann, M., Scholz-Reiter, B., de Beer, C., Austerschulte, L., Effects of Autonomous Cooperation on the Robustness of International Supply Networks – Contributions and Limitations for the Management of External Dynamics in Complex Systems, LogDynamics International Conference, Bremen, 2008, 241-250.

[12] Windt, K., Hülsmann, M., Changing Paradigms in Logistics - Understanding the Shift from Conventional Control to Autonomous Cooperation and Control, Understanding Autonomous Cooperation & Control - The Impact of Autonomy on Management, Information, Communication, and Material Flow, 2007,.4–16.

[13] Scholz-Reiter, B., de Beer, C., Freitag, M., Jagalski, T., Bio-inspired and pheromone-based shop-floor control, International journal of computer integrated manufacturing, 21(2), 2008, 201-205.

[14] Windt, K., Becker, T., Applying Autonomous Control Methods in Different Logistic Processes - A Comparison by Using an Autonomous Control Application Matrix. Proceedings of the 17th Mediterranean Conference on Control and Automation, 2009.

[15] Armbruster, D., de Beer, C., Freitag, M., Jagalski, T., Ringhofer, C., Autonomous Control of Production Networks Using a Pheromone Approach, Physica A, 363(1), 2006, 104-114.

[16] Scholz-Reiter, B., Jagalski, T., Bendul, J.: Autonomous control of a shop floor based on bee’s foraging behaviour, First International Conference on Dynamics in logistics. LDIC 2007, Bremen, 2008, 415-423

[17] Crainic, T.G., Service network design in freight transportation, European Journal of Operational Research, 122(2), 2000, 272-288

[18] Foley, R.D., and McDonald, D.R., 2001. Join the Shortest Queue: Stability and Exact Asymptotics. The Annals of Applied Probability, 11(3), 569-607.

[19] Parunak, H.V., "Go to the ant": Engineering principles from natural multi-agent systems, Annals of Operations Research, 15, 1997, 69-101.

[20] Peeters, P., van Brussel, H., Valckenaers, P., Wyns, J., Bongaerts, L., Kollingbaum, M., Heikkilä, T., Pheromone based emergent shop floor control system for flexible flow shops, Artificial Intelligence in Engineering, 15 (4), 2001, 343–352.