Modelling and Analysis of Autonomously Controlled Production Networks

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Abstract: To cope with increasing internal and external dynamics of production networks, a decentralized and flexible autonomous control approach seems to be promising. This paper presents a dynamic model of a production network with geographically dispersed facilities and fixed transport schedules. It investigates the influence of local autonomous control methods on integrated production and transport processes and shows that the application of autonomous control may improve the handling of internal and external dynamics.

Keywords: production network, autonomous control, discrete event simulation

1. INTRODUCTION

Manufacturing companies are more and more challenged by increasing market dynamics: During the recent years, customers increasingly demand highly customized products, stipulated delivery times are decreasing and the adherence to delivery dates becomes critical. Manufacturing enterprises have to adapt to these changes rapidly. To sustain competiveness companies concentrate more on their core competences on one hand. On the other hand they have to establish close cooperation in order to fulfil the whole demand of their customers. Different cooperation concepts, like virtual enterprises (Martinez et al. 2001, Camarinha-Matos 2003) or production networks (Wiendahl et al. 2002) have been developed to enable companies to react promptly to dynamic changes. Production networks focus on integrated planning of geographical dispersed and company spanning processes as well as the planning of usage of common resources. In a network of geographic dispersed production plants, additional tasks and challenges for production planning and control (PPC) arise, e.g. the assignment of orders to plants. Under highly dynamic and complex conditions current PPC methods cannot cope with disturbances or unforeseen events in an appropriate manner (Kim et al. 2004). A promising approach to this problem is the introduction of autonomous control strategies. Autonomous control enables decentralized coordination and decision making of intelligent logistical objects within a logistic system. Implementation of autonomous control may increase the robustness of a logistic system against external and internal disturbances by influencing the behaviour of the system in a positive manner. Furthermore, it has been shown that autonomous control methods can help to improve the logistics performance of production systems (Scholz-Reiter et al. 2005).

Due to the high level of complexity of a production network the implementation of autonomous control strategies seems to be an appropriate approach to increase the flexibility and robustness. This paper investigates a production network scenario with varying production control and transport strategies and shows that the application of autonomous control strategies improves the handling of external and internal disturbances.

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 wide 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 et al. 2007). Thus, the idea of autonomous cooperating logistic processes is to generate decentralized planning and control methods, which allow intelligent logistic objects to route themselves through a logistical network according to their own objectives (Windt et al. 2005). In this respect, intelligent logistical objects are physical objects (e.g. machines, parts, etc.), as well as immaterial objects like production orders. By interacting with other intelligent objects, they are able to gather information about the current local system states and to use this information for decentralized decision making (Windt 2006).

First approaches of autonomous control of production logistics have been developed: These models prove that autonomous control methods can improve the ability of a logistic system to handle dynamics as well as the logistic performance of the system (Armbruster et al. 2006; Scholz-Reiter et al. 2007a).

As far as production networks are concerned, a first autonomous control approach was formulated: This approach investigates the material flow between two plants using autonomous control methods within a production network (Scholz-Reiter et al. 2007b).

3. PRODUCTION NETWORKS

Production networks are cross-company cooperation between geographically dispersed facilities, which aim on the mutual use of common resources and integrated planning value added processes (Wiendahl et al. 2002).

According to this definition, new task and challenges appear in production networks: enterprises within a production network are forced to generate concepts for tasks like the choice of new partners, design of the network, product development and production planning and control (Sydow 2006). PPC in production networks has to deal with additional tasks as well: Due to the high flexibility of these networks complex interdependencies between production processes in different plants can occur, e.g. allocation problems for parts, which can be process in different plants or planning of transports and transport capacity (Sauer 2006; Alvarez 2007). Thus, a shift from pure core tasks of PPC to an integrated planning of synchronisation within the network, including planning of sales, inventory, and resources is necessary (Wiendahl et al. 2002).

Uncertainty of lead times and nervousness of schedules are already issues for single plants, but these issues are even more important for production networks. Thus, new approaches dealing with the complexity and dynamic of production networks are necessary (Erengünc et al. 1999; Nof et al. 2006). Especially integrated solutions, which cover local as well as production plant spanning logistic activities, seem to be promising for production networks.

This paper presents a simulation model of a production network to analyse the behaviour and dynamics of multiple coupled plants. It investigates both, the effect of autonomous control strategies on the dynamics of production networks and the behaviour of autonomously controlled production networks with respect to external and internal dynamics.

4. PRODUCTION NETWORK SCENARIO

A production network with j×k different production plants is considered, which is partitioned in j stages with k production plants per stage. Every plant in this network consists of a shop floor with m production stages and n production lines of buffers and machines (Fig. 1), which are able to process a various set of jobs. The plants are connected via transport systems (Fig 1). After being processed in a plant the semi-finished products are buffered, until an order for transportation is generated and a truck carries them to the next plant for further processing. The transport orders are generated in fix time intervals, i.e. the transport interval (TI).

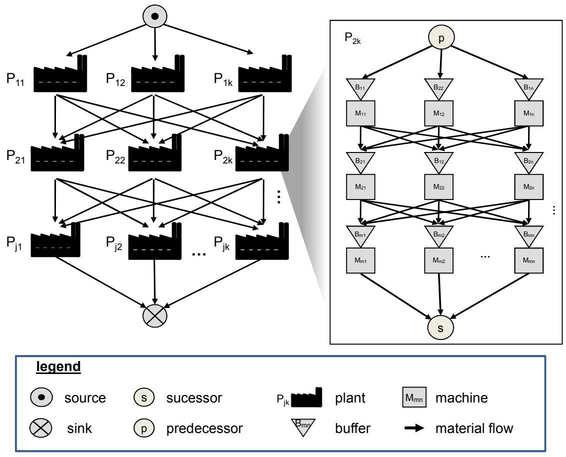

Fig. 1. Production network with j×k plants

To analyse this scenario a discrete event model has been developed. In order to deal with the complexity the considered model is reduced to six production plants, which are collocated in four stages. Each plant comprises a shop floor with 3×3 machines. On the first and on the last stage of the production network, there is only one plant. On stages two and three there are two parallel plants, which are able to perform the same operations. The plants are even distributed as far as the geographical distance is concerned: between a plant and its successors the distance is assumed to be 140 km (Table 1).

Table 1: distance matrix [km]

	To plant					
Plant	P_{11}	P_{21}	P_{22}	P_{31}	P_{32}	P_{41}
P_{11}	-	140	140			
P_{21}		-		140	140	
P_{22}			-	140	140	
P_{31}				-		140
P_{32}					-	140
P_{41}						-

The velocity of a truck is assumed to be 70 km/h. Thus, transports take 2 h. There are no capacity limitations among the trucks.

Jobs running through this production network have to start in the plant at stage one and have to pass all other stages once. There are three types of jobs (Type A, Type B and Type C) with different processing times at each production line on the shop floor level. Table 2 shows the different processing times for each product type on every production line of every plant.

Table 2: Processing times of all job types and lines

Plant	P_{11}; P_{41}			P_{21}; P_{22}; P_{31}; P_{32}		
Type \ Line	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

New jobs arrive at plant P_{11} with a variable arrival rate. To model demand fluctuations this arrival rate of new jobs is set as a sine function (1). The simulation time is 30 days. The arrival rates of each job type have a phase shift φ of 1/3 respectively 2/3 of a period.

$$\lambda(t) = \lambda_m + \alpha \cdot \sin(t + \varphi) \quad (1)$$

The mean arrival rate is set to λ_m=0.4 1/h. Due to this arrival rate in average every 2:24 h a new part of each type enters the production network. The intensity of these seasonal fluctuations is determined by the amplitude α of the sine function, which can be varied in several simulation runs (between 0.15-0.24 1/h). A similar approach for modelling a shop floor, i.e. a single plant, can be found in (Scholz-Reiter et al. 2005).

5. PLANNING AND CONTROL METHODS

For benchmarking one conventional planning method and two different autonomous control strategies were implemented: a centralized planning method (CP), the queue length estimator (QLE) and a pheromone based (PHE) method.

CP assigns the jobs on the shop floor level according to the machines with the shortest processing times for this type of job. This assignment is predetermined. Thus this type of planning can be seen as a conventional planning method.

QLE is based on the comparison of buffer levels of each production line. Intelligent parts using this method have the objective to reduce their throughput time (TPT). To meet this objective the parts may choose a line for processing. Parts finished at a certain machine are able to compare the buffer levels of the next production stage. They choose the line with minimal workload. For a further description of QLE see (Scholz-Reiter et al. 2005).

The second autonomous control strategy is the pheromone based approach PHE. It is based on the idea to imitate the process, how ants mark 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 pheromone (Parunak 1997). To transfer this process to the production scenario parts leave information about their TPT at a machine. Parts entering a stage of the shop floor compare this artificial pheromone concentration by computing average TPT data of the last five orders and choose a line. Thus the pheromone concentration depends on queue times and processing times of previous jobs. To model the evaporation process of natural pheromones a moving average of TPT is used. Similar approaches for modelling pheromone based autonomous control methods can be found in (Peeters et al. 2001; Armbruster et al. 2006).

Parts, which finished processing in the Plants P_{11} P_{21} and P_{22}, have two possible successor plants for further processing (Table 1). Outgoing semi-finished products are sent to successor plants in an alternating order.

6. SIMULATION AND RESULTS

Several simulation runs have been set up in order to analyse the impact of external and internal disturbances on this production network. External changes are implemented by means of varying the amplitude α. System internal changes are modelled by variations of TI. The benchmarks of the logistic performance are based on the comparison of total TPT. In this context, total TPT represents the time, which is spent by the respective product to pass the whole production network starting at plant P_{11} and ending at plant P_{41}. Mean total TPT is used in section 6.1 to compare the impact of internal and external changes for all three control methods. The Section 6.2 focuses on analysis of the dynamics, which is cause by the three control methods. Therefore the standard deviation of total TPT and TPT of single plants is used.

6.1 Impact of external and internal disturbances

Fig. 2 shows the mean total TPT of the production network for CP. It is plotted against the TI. Each dot represents a simulation run with an associated transport interval and an amplitude α= 0.15, 0.18, 0.21 and 0.24 respectively.

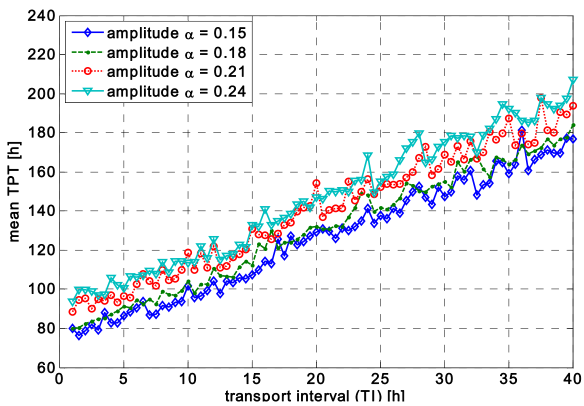

Fig. 2. Mean TPT against TI for CP

Fig. 2 shows an increasing trend of mean total TPT for larger TIs. The TI rises in equidistant steps of 0:30 hours in every simulation run. It can be noticed, that the increase of mean TPT is bigger than the increase of TI. On the other hand it can be observed, that the increase of mean TPT is on average 2.68 h. This implies that increasing TIs causes dynamic effects inside the network. The bigger the TIs the more semi-finished products have to be stored in the outgoing buffers of every plant and trucks have to carry more parts to the next plant. This causes a transitional overload to the successor plant. To analyse this effect in depth, Fig. 3 exemplary shows the TPT of product type A for the plant P_{21} for TI = 4 h and TI = 12 h with α=0.21/h.

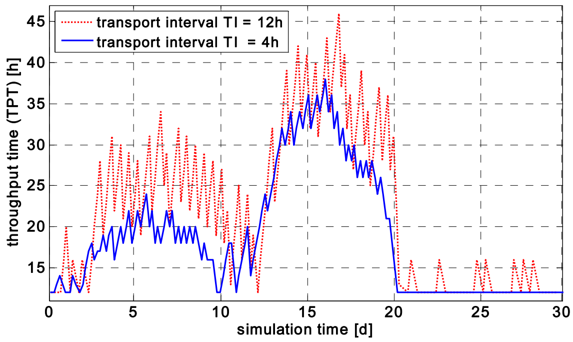

Fig. 3. CP: TPT for TI = 4 h and TI = 12 h

According to Fig. 3 TPT for TI = 4 h is obviously smaller than for TI = 12 h indicating a smaller workload in the first case. This effect can be found at each plant. Increasing TI leads to a rising total TPT for two reasons: The first is intrinsically in TI: Due to the rising TI the TPT has to rise as well. Secondly, an increasing TI leads to a temporary overload of the successor plant and causes higher TPT.

Additionally, Fig. 2 shows that the mean total TPT increases stepwise with increasing values of α. In this respect autonomous control strategies can perform better: Fig. 4 presents the mean total TPT for QLE.

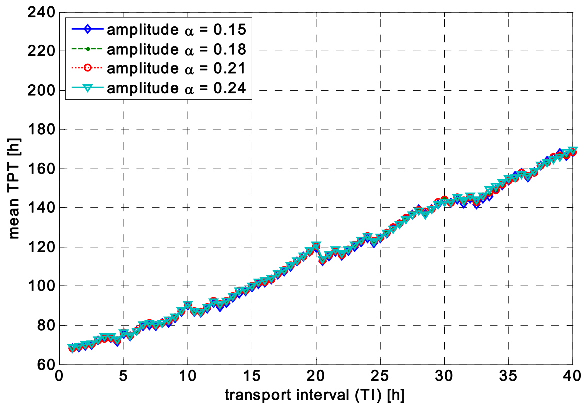

Fig. 4. QLE method: mean throughput times against TI

The impact of varying α is significantly smaller than for the preplanned scenario (Fig. 2). The maximum difference between mean total TPT in Fig. 4 can be found at TI = 32:30 h and α = 0.15 1/h respectively α = 0.24 1/h: 3:25 h or 1.72 %. In the CP scenario (Fig. 2) this difference is 33:13 h, a deviation of 20.8 % respectively. Notice that the curves in Fig. 4 are almost overlapping in sharp contrast to the curves in Fig. 2.

Furthermore Fig. 4 shows a quasi-linear trend for mean TPT. As already mentioned: Mean total TPT is depending on TI. This effect occurs in case of QLE as well (Fig. 4): high values of TI lead to a temporary overload as well. But when comparing QLE to CP, it can be noticed that mean total TPT in Fig. 4 is on average 20:08h (14.84%) lower for each amplitude α. Thus, it can be concluded that the autonomous control strategy QLE can handle temporary overload situations far better than conventional control methods.

The second autonomous control strategy, i.e. PHE, performs slightly different. Compared to CP (Fig. 2) the absolute values of mean total TPT are also smaller for all amplitudes up to a TI of 35 h (Fig. 5). Compared to QLE (Fig. 4) the mean TPT of PHE is slightly bigger. When analysing the effects of market dynamics, one can see that the influence of increasing the amplitude of the arrival rate α is smaller than in conventional planed case: Here the maximum span between α = 0.15 and α = 0.24 is 30:38h, a difference of 15.21 %.

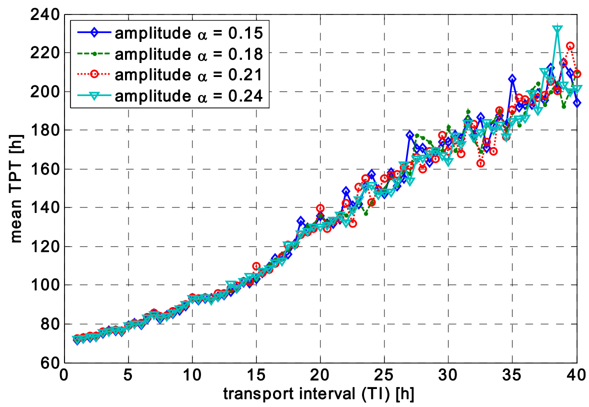

Fig. 5. PHE method: mean TPT against TI

For small values of TI the behaviour of PHE can fairly be compared to the behaviour of QLE. For bigger values of TI, say TI ≥ 19 h, a turning point can be observed (Fig. 4 and Fig. 5). Starting from this point, the PHE method influences the dynamic behaviour of the global system in significantly different than the QLE method. In contrast to the QLE method (Fig. 4) the different curves for the PHE method (Fig. 5) start to diverge for TIs bigger than 19 h. This effect can be explained as follows: For TI ≥ 19 h the impact of varying the amplitude α becomes more important for the PHE. As already stated, increasing TI leads to temporary overload situations. The PHE method can not cope with the amount of parts entering the plant for TI ≥ 19 h as good as below this value.

6.2 Impact of control methods

To sum up the results of the simulations so far: An autonomously controlled production network seem to be able to react more robust on both, market fluctuations (changes of the arrival rate) and internal disturbances (i.e. variations of TI) than conventional and centralised planning methods. The standard deviation (STD) of TPT is an instrument to measure the robustness of logistic systems, i.e. the dynamic behaviour regarding internal or external changes. Fig. 6 presents the standard deviation of mean total TPT for the three methods and an amplitude α = 0.18 1/h. The difference in STD of the CP and QLE method is 58.1 %, respectively 36.96 % compared the PHE method.

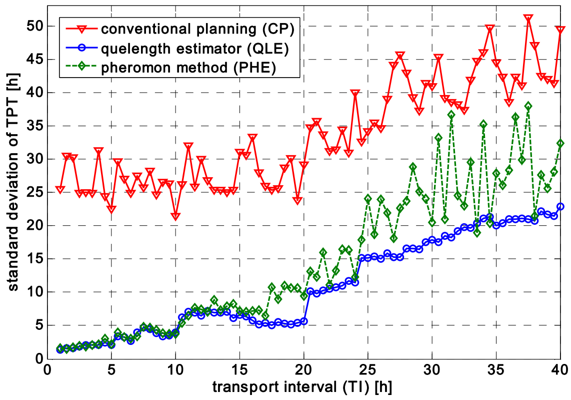

Fig. 6. STD against TI for all methods (α = 0.18 1/h)

Furthermore, Fig. 6 shows an increasing trend of STD for all three methods. Up to a TI of 13:30 h the autonomous control methods have a comparable STD. Beyond this point the STD of PHE method increases faster then the one of QLE. At a TI of 19 h the curve for STD of PHE starts to alternate, confirming that the performance changes suddenly at this point. In comparison to the curves of the other methods the QLE methods shows also an increasing trend, but no alternating behaviour for a rising TI.

The results presented above show that autonomous control methods may cause sudden changes of total system behaviour under certain conditions introducing an intrinsic dynamic behaviour or even chaos. Especially the results concerning the PHE method show that dynamic factors, i.e. increasing TI, may change the behaviour of the global system rapidly hence make it unpredictable. On the other hand, autonomous control methods may improve the performance of the global system and the robustness of a production network regarding external and internal changes. To understand these effects a more detailed view on the single plants of the production network is necessary.

Fig. 7 and Fig. 8 present TPT for product type A of each single plant (P_{21}; P_{22};P_{31};P_{32}) in a simulation run with TI = 9 h and α = 0.15 1/h for the CP and the QLE method.

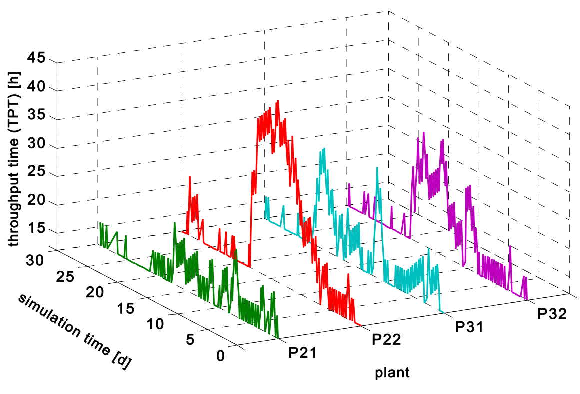

Fig. 7. CP: TPT for parallel plants against simulation time

When incorporating CP all plants show phases with temporary overloads (Fig. 7). In these overload situations the TPT rises constantly, until the inventory can be processed. The point in time when a certain plant reaches its maximum TPT differs from plant to plant. For example plant P_{22} reaches its maximum of TPT = 44:30 h at day 13. On the other hand plant P_{31} has its maximum value of TPT (31:30h) at day 11. Fig. 7 reveals that every CP plant reacts in a different way. Additionally, the absolute values of maximum TPT differ: The difference between plant P_{22} and plant P_{31} is 12:30 h or 28.4 %. There is no harmonisation between parallel plants when CP is implemented.

Fig. 8 presents the TPT for the QLE method. In contrast to Fig. 7 the curves in Fig. 8 are significantly smoother. The distribution peaks of TPT are spread over the whole simulation time and maximum peaks are much lower than for the CP method (Fig. 7). The difference between highest and lowest maximum value of a plant is 1:28 h, which is a difference of only 7.5 %. Curves in Fig. 8 are more balanced than the curves in Fig. 7: The autonomous control method QLE can harmonise the behaviour of parallel plants.

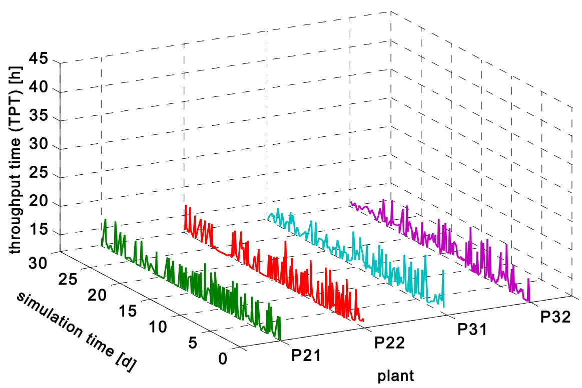

Fig. 8. QLE method: TPT for parallel plant against simulation time

Table 3 summarizes these results. It presents the mean TPT and the STD for the three methods. This data was recorded in a simulation run with α = 0.15 1/h and TI = 9h.

Table 3: Performance for different control methods

	CP [h]		QLE [h]		PHE [h]	
Plant	Mean	STD	Mean	STD	Mean	STD
P_{11}	8:23	3:18	6:52	0:53	8:39	0:55
P_{21}	15:08	3:01	13:56	2:02	14:20	2:18
P_{22}	22:43	7:32	14:51	2:11	14:54	2:27
P_{31}	16:31	4:40	13:52	1:45	14:43	2:10
P_{32}	17:52	4:52	13:51	1:48	14:33	1:54
P_{41}	8:48	2:12	9:31	2:34	10:22	2:43

Table 3 shows that the standard deviation of TPT of both autonomous control methods is averagely lower than of conventionally planned method. Thus, successor plants get smoothed and uniform inputs, which leads to a uniform performance of this plant. In conventionally planned scenarios the mean TPT values vary within the plants, thereby affecting the successor plants.

7. SUMMARY AND OUTLOOK

Autonomous control methods can lead to an improvement of the logistic performance of production networks and enable the system to adapt to external and internal dynamics. It was shown that autonomous control can smooth out the output of single plants and harmonize the behaviour of parallel plants. This encourages further research in this area. Especially the effects of system size, pull-strategies for transport and the introduction of multimodal transport are promising topics for future analysis. Furthermore, the design of new autonomous control strategies, which lead to a desired behaviour of a given logistic system opens up new areas of research concerning the performance and the synchronisation of production networks.

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