CARV 2007

Analysing the Dynamics caused by Autonomously Controlled Logistic Objects

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Abstract: This paper focuses on the analysis of the dynamics that is caused by autonomously controlled logistic objects. On the one hand the introduction of autonomous logistic objects aims at the improvement of the systems stability and adaptability in situations of disturbances and/or external dynamics. This should be achieved by emergent effects and the interaction of the logistic objects. On the other hand this could cause different forms of dynamics like oscillations, quasi oscillations or even chaotic behaviour of the logistic target figures like throughput time and work in process. In this paper different autonomous control methods are compared using frequency analysis. It was discovered that different autonomous control methods can lead to different forms of dynamics which is of interest for planning and control systems that apply autonomous control methods.

Keywords: Autonomous control, production planning and control, dynamics, logistics, discrete event simulation

1 Introduction

Autonomous control is one of the large research trends in production planning and control and logistics in general (Armbruster, et al., 2006), (Hülsmann, et al., 2006), (Scholz-Reiter, et al., 2005). In this context, autonomous control means the decentralised coordination of intelligent logistic objects and the routing through a logistic system by the intelligent parts themselves, which is in accordance to the definition of autonomous control (Hülsmann, Windt, 2007).

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The motivation for doing research on autonomous control is the assumption that by shifting the ability to render decisions to the logistic object itself, the adaptiveness, the flexibility and therefore the robustness as well as the performance of the logistic system could be enhanced. Research done by Ueda (Ueda, et al., 1994), Prabhu and Duffie (Prabhu, Duffie, 1995) and van Brussel (van Brussel, et al., 1994) motivates this assumption. In earlier work, the authors have developed a discrete event simulation model to analyse the effects of different autonomous control strategies on the behaviour of a logistic system (Scholz-Reiter, et al., 2006). While the focus in this earlier work laid more on the performance and the stability of the logistic system, this paper deals with the influences of autonomous control strategies on the systems dynamics.

2 Shop Floor Scenario and Simulation Model

To compare the different autonomous control methods, a shop floor scenario is needed that allows for the application of autonomous control methods and is general enough to be valid for different scenarios and different classes of shop floor types. For these reasons, a shop floor model in matrix format has been chosen (Fig. 1). Subsequent productions steps are modelled vertically, while parallel stations are able to perform resembling processing steps.

At the source the raw materials together with the orders for each product enter the system without any type of WIP control. Each product class has a different production plan, i.e. a list of processing steps that have to be fulfilled on the related machines. In case of overload the parts can decide autonomously to change the plan and to use a parallel machine instead. For rendering these decisions the parts follow predefined algorithms that are called autonomous control methods. The final products leave the system at the drain.

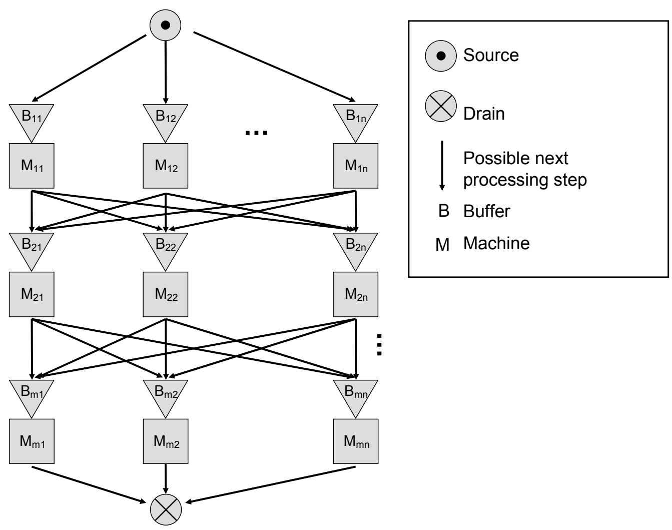


Fig. 1 Matrix model of a shop floor

The cycle time of a machine is set equally two hours for all part types. The transport times are regulary distributed between zero and one hour while the buffer size is infinite. Using the discrete event simulation software eM-Plant, the production logistic matrix model has been implemented to simulate different scenarios with different parameter constellations. Thereby the functionality of eM-Plant has been expanded by programming methods that create automatically the different simulation scenarios of the MxN Matrix-Model such as different sized scenarios from 2x2 to 9x9 machines can be automatically created and are ready for simulation.

The results in this paper are created using a 5x5 machines scenario. The scenario includes transportation times, i.e. to switch to a different machine takes an amount of time related to the distance between the machines.

Furthermore, every part is given a due date following a normal distribution oriented on the mean throughput time that is determined from the first two months of simulation.

3 Autonomous Control Strategies

Queue length estimator

The first method called queue length estimator compares the actual buffer level at all the parallel machines that are able to perform its next production steps, i.e. the direct succesors refering to its production plan. Therefore, the buffer content is not counted in number of parts but the parts are rated in estimated processing time and the actual buffer level 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 level i.e. the estimated waiting time until processing and chooses the buffer with the shortest waiting time (Scholz-Reiter, et al., 2005).

Pheromone method

The second method does not use information about estimated waiting time, i.e. information about future events but uses data from past events. This method is inspired by the behaviour of foraging ants that leave a pheromone trail on their way to the food. Following ants use the pheromone trail with the highest concentration of pheromone to find the shortest path to the food. In the shop floor scenario this behaviour is imitated in a way that whenever a part leaves a machine, i.e. after a processing step is accomplished, the part leaves information about the duration of processing and waiting time at the respective machine. The following parts use the data stored at the machine to render the decision about the next production step. The parts compare the mean throughput times from parts of the same type and choose the machine with the lowest mean duration of waiting and processing. The amount of data sets that are stored define the up-to-dateness of the information. This number of data sets can be used to tune the pheromone method. The pelacement of older data sets resembles to the evaporation of the pheromone in reality (Scholz-Reiter, et al., 2006).

Due date method

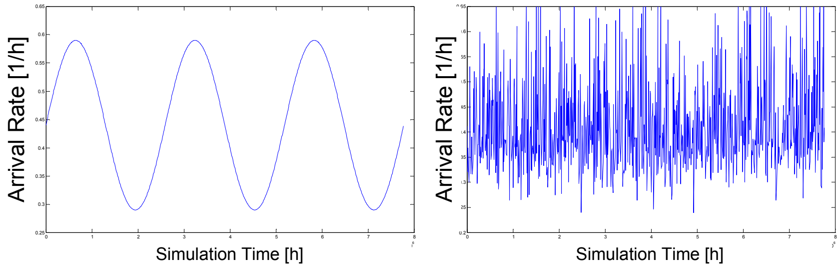
The due date method is a two step method. When the parts leave a machine they use the queue length estimator to choose the machine with the lowest buffer level. Within the buffer the due dates of the parts are compared and the part with the most urgent due date is chosen to be the next product to be processed.

4 Simulation and Analysis

To model a highly dynamic market situation, the demand for the different products is set as an oscillating curve with situation of over and under load. A short extract of three month of the resulting arrival rate is shown in Fig. 2.a. Fig. 2.b shows the corresponding arrival rate if the parts enter the system with the same mean arrival rate but following a normal distribution. For these two different arrival characteristics the resulting dynamics caused by the three different autonomous control methods is analysed. Different forms of dynamics could be:

- chaos or deterministic chaos means an aperiodic deterministic behaviour, which is very sensitive to its initial conditions, i.e. infinitesimal perturbations of boundary conditions for a chaotic dynamic system originates unpredictable variations of the systems behaviour
- periodic behaviour of a system means that the system reaches the same values after some definite *period* of time.
- quasiperiodic behaviour means that a system is showing periodic characteristics (with multiple frequencies) without ever exactly coming back to the same states (in phase space).
- stochastic behaviour means that the system shows unpredictable fluctuations.

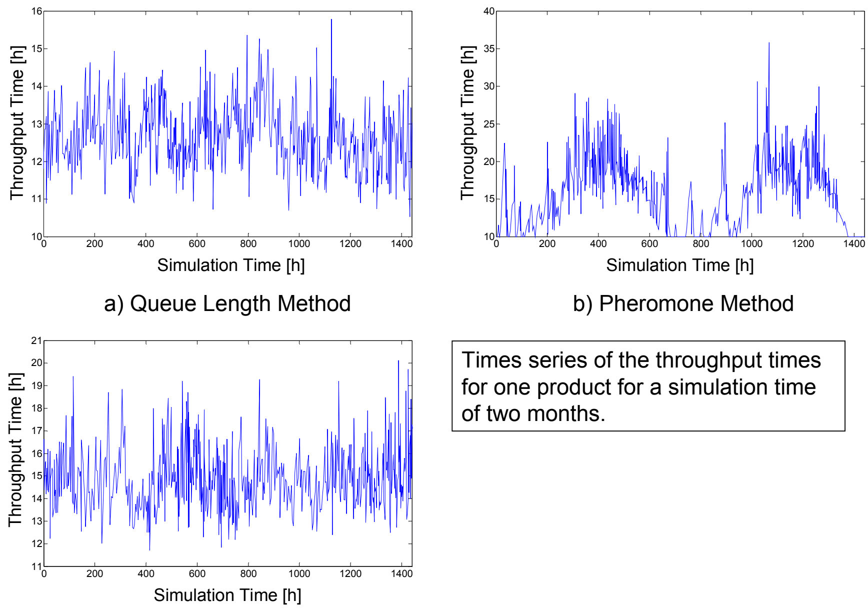
To distinguish between the different forms of dynamics Fig. 3. shows extracts of the resulting throughput times for a simulation time of two months with sinussoidal input. Shown are the mean throughput times for one product for the three different autonomous control methods. The first month is cut of to avoid transient effects. Fig. 3.a shows the throughput time for the queue length estimator, Fig. 3.b shows the resulting throughput times for the pheromone method, Fig. 3.c shows the resulting throughput times for the due date method. To analyse the resulting dynamics of the system a frequency analysis of the time series as a discrete fourrier transformation has been done.



a) Sinussoidal Arrival Rate b) Stochastic Arrival Rate

Fig. 2. Input, sinusoidal and stochastic

There are many more tools in nonlinear time series analysis, but the frequency analysis is adequate to distinguish between periodic, quasi periodic and chaos/stochasticity. To distinguish between chaotic and stochastic dynamics is not possible with ordinary frecquency analysis and is not topic of this paper.

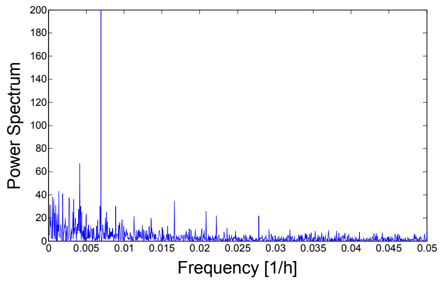


a) Queue Length Method b) Pheromone Method

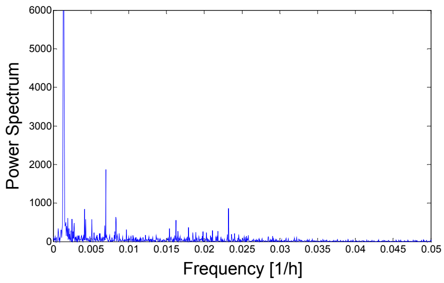
c) Due Date Method

Fig. 3. Throughput time for three different autonomous control strategies

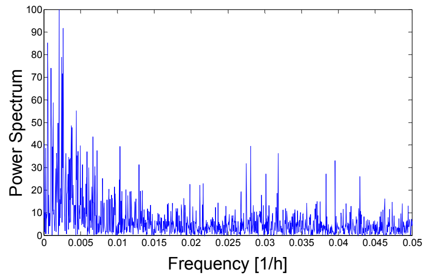
One realises that the time series of the pheromone method shows a periodic behaviour, while the time series of the queue length estimator and the due date method show a more complicated structure. Furthermore, the mean values and the variance of the time series from the pheromone method is significantly higher than that of the queueu length estimator which has also been analysed in earlier work (Scholz-Reiter, et al., 2006). The larger the amount of data is, the better are the results of the disctrete fourier transformation. Therefore a simulation time of three years has been chosen. Fig. 4. shows the corresponding power spectra of the throughput time series. Power spectra answer the question which frequencies the signal contains. The answer is in the form of a distribution of power values as a function of frequency, where "power" is a relative amount correlated with the average of the signal. In the frequency domain, this is the square of the magnitude of the fourrier transformation.



a) Queue Length Method (Que)



b) Pheromone Method (Phe)



c) Due Date Method (Due)

	Que	Phe	Due
Frequency [1/h]	0,0045 0,007 0,016	0,0015 0,007 0,023	-
Period [h]	222 143 63	700 143 44	-

Fig. 4. Fourrier transformation of the time series from Fig. 3

Periods of 700h, 143h and 44h are found within the pheromone signal. The first and highest peak in the signal resembles the period of 700h or one month, which is the simulation period and which is identical with the period of the arrival rate. The other two dominating frequencies of 143h and 44h, which are approximately 2 and 6 days, can not be explained by the incoming sinusoidal signal and could be called emergent.

Emergent behaviour cannot be explained by the features of the single objects and are properties of the overall system that are caused by the interaction of the autonomous objects (Ueda, et al., 2004) (Küppers, Krohn, 1992). Here, the pheromone method gives no hint why the system should oscillate with a period of 2 or 6 days. This oscillation can be only understood through the interaction of the parts via their surrounding, in this case the information that are left at the machines. It seems to be that the parts oscillate between fast and not so fast solutions to get through the network which. This could be influenced by the evaporation constant which is a measurement of the up-to-dateness of the information that is used. This evaporation constant is a mean to tune the pheromone rule and its amount has an effect on the performance of the system (Peeters, et. al., 2001). The effects of the evaporation constant on the resulting dynamics will be one of the topics of future research.

The power spectrum of the queue length estimator shows three dominating periods at 222, 143 and 63 hours. These frequencies can also not be explained by the oscillation of the arrival rate and have also to be called emergent. In this case, it is not clear how these frequencies depend on the arrival rate. The simulation period of 700 h does not appear because their is no update of information like in the pheromone rule so that the effect described in Peeters et. al. is not found here. Interesting is that the period of six days appears here again which gives a hint to a system inherent characteristic. Nevertheless, if the stochastic arrival rate is applied, the frequencies disappear and the system shows stochastic behaviour.

In the spectrum of the due date method there can hardly be any single frequency peaks identified. In this case, the dynamics tend more to chaotic behaviour than in the other two cases. This shows that the ordering by due date limits the influence of the outside dynamics and results in chaotic behaviour when in a totally deterministic system a deterministic periodic signal is used as input.

The stochastic arrival rate results for all the three methods in a stochastic behaviour and no single peaks in the power spectra could be observed.

5 Conclusion and Outlook

Analysing the dynamics of the time series that are caused by autonomous control methods give a hint to the behaviour of the overall system. In this paper we have discovered different forms of dynamics and different oscillating periods that can not be explained by the incoming oscillating arrival rate nor through the features of the single objects. This behaviour of the system can be called emergent, because it is caused by the interaction of the autonomous parts and can not be explained by the features of the single objects.

The sinussoidal signal that is induced into the system via the arrival rate can cause periodical behaviour of the overall system. This is found for the pheromone method and for the queue length estimator. The due date method shows no periodical behaviour at all. But the interesting fact about the found oscillations are the emergent frequencies. Such periodic behaviour that is not predictable from the systems structure or the incoming dynamics is of great interest for planning and management decisions.

The knowledge about the resulting dynamics is essential before transferring autonomous control strategies to real life systems, because unforeseen periodic or chaotic behaviour can cause serious problems and prevents the predictability of the system’s behaviour. Therefore, it is essential to know in advance what kind of dynamics is caused by which autonomous control method.

Furthermore, the stochastic arrival rate has so far not shown any periodic behaviour in the resulting signals. Future work concentrates on finding scenarios where autonomous control methods lead to periodical behaviour while no periodic signal is introduced in the system via external dynamics.

6 Acknowledgements

This research is founded by the German Research Foundation (DFG) as part of the Collaborative Research Centre 637 "Autonomous Cooperating Logistic Processes: A Paradigm Shift and its Limitations" (SFB 637) at the university of Bremen.

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