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Modelling and Analysis of Autonomous Shop Floor Control

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Abstract
To manage the increasing dynamics inside and outside a production system, a decentralised and autonomous control of shop floor logistics is a promising approach. For developing and benchmarking such autonomous control methods, dynamic models are essential. The paper introduces the idea of autonomous logistic processes and presents a dynamic simulation model of a shop floor with both a conventionally planned and an autonomously controlled scenario. The decentralised and autonomous control strategy bases on autonomous elements that are able to make decisions by themselves using distributed local information. The simulation model is used for analysing the system's dynamics at varying workloads. The logistic performance is analysed by comparing throughput times for the different logistics situations and during expected and unexpected disturbances.

Keywords:
Production, Control, Autonomy

1 INTRODUCTION

Due to increasing market dynamics, Production Planning and Control (PPC) has become more challenging for manufacturing companies. Today, production plans have to adapt quickly to changing market demands while conventional PPC methods cannot handle unpredictable events and disturbances in a satisfactory manner [1].

One reason is that in practice the complexity of centralised architectures tends to grow rapidly with size, resulting in rapid deterioration of fault tolerance, adaptability and flexibility [2].

To solve this dilemma and to manage the dynamics inside and outside the production system the development of decentralised and autonomous control strategies is a promising research field [3]. Here autonomous control means a decentralised coordination of intelligent logistic objects (parts, machines etc.) and the routing through a logistic system by the intelligent parts themselves.

Those intelligent items follow autonomously decision rules that are based on local information. The dynamics of such a system depends on the decision-making processes and produces a global behaviour of the system that has new emerging characteristics. Thereby the interactions and interdependencies between local and global behaviour are not trivial. Remember a colony of ants where a single ant has no idea about the whole colony. It only acts by a few simple rules but the entire colony consisting of thousands of ants is able to build gigantic nests, to find shortest paths between food and nest etc. This self-organisation is a so-called emergent behaviour of a complex dynamic system and not derivable from single characteristics [4].

2 AUTONOMY IN PRODUCTION LOGISTICS

The concept of autonomous control requires on one hand logistic objects that are able to receive local information, process this information, and make a decision about their next action. On the other hand, the logistic structure has to provide distributed information about local states and different alternatives to enable decisions generally. These features will be made possible through the development of Ubiquitous Computing technologies [5].

The application of autonomous control in production and logistics can be realised by recent information and communication technologies such as radio frequency identification (RFID), wireless communication networks etc. These technologies facilitate intelligent and autonomous parts and products which are able to communicate with each other and with their resources such as machines and transport systems and to process the acquired information. This leads to a coalescence of material flow and information flow and enables every item or product to manage and control its manufacturing process autonomously [3]. The coordination of these intelligent objects requires advanced PPC concepts and strategies to realise autonomous control of logistic processes. To develop and analyze such autonomous control strategies dynamic models are required. In the following a shop floor scenario introduced by Scholz-Reiter et al. [6] is modified and used to model autonomous processes in a flexible production scenario.

3 SHOP FLOOR SCENARIO

The considered shop floor scenario is a dynamic flow-line manufacturing system. It consists of n parallel production lines each with m machines M_{ij} and an input buffer B_{ij} in front of each machine (see Figure 1). Every line processes a certain kind of product A, B, … X by m job steps. The raw materials for each product enter the system via sources; the final products leave the system via drains.

In this shop floor, two different logistic situations will be compared. In the first case, each line processes its associated product independently from the other lines. Here, the way of the single parts through the machines is pre-determined by a hierarchical planning process. This case will be called conventional planning in the following.

In the second case, the production lines are coupled at every stage. Furthermore, every line is able to process every kind of product within a certain stage. The processing times for each product are higher on foreign lines than on their own. This structure allows the parts to

switch lines at every stage. The decision about changing the line is made by the part itself on the basis of local information about buffer levels and expected waiting times until processing. Thereby, the parts take into account that the processing times are higher on foreign lines than on their own. This logistic strategy will be called autonomous control because the parts are autonomous in their decision and there is no superior controller who decides in which way the parts will be processed [7].

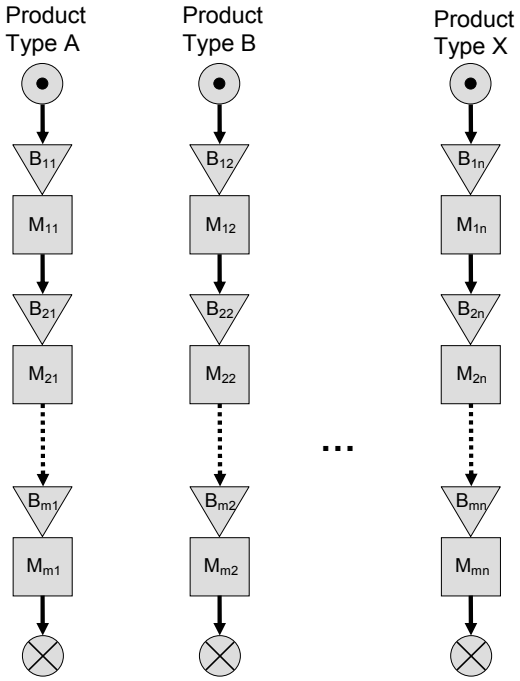

Figure 1: mxn machines shop floor scenario.

In the following the dynamics and performance of both the conventionally planned and the autonomously controlled shop floor will be analysed using a dynamic simulation model.

4 DISCRETE-EVENT SIMULATION MODEL

To handle the complexity of the shop floor the described scenario is reduced to 3x3 machines, i.e. three production lines each with three stages. Every line processes a certain product A, B, and C by three job steps. This shop floor structure is modelled using a discrete-event simulation software tool.

4.1 Conventional Planning

The first case to be investigated is the conventional situation where the lines work independent from each other and a plan determines which job step will be done at which machine. Each line is balanced i.e. every machine within a line has the same processing rate of 0.5 parts per hour. From these processing rates result processing times of 2 hours for processing one part at one machine. The processing times and the resulting processing rates are shown in Table 1.

To analyse the system's behaviour at varying demand and workload fluctuations, an arrival function $\lambda(t)$ is defined and set as a sine function:

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

Stage m	Processing times [h:min] and processing rates [1/h] at production line n		
	1	2	3
1	2:00 / 0.5	2:00 / 0.5	2:00 / 0.5
2	2:00 / 0.5	2:00 / 0.5	2:00 / 0.5
3	2:00 / 0.5	2:00 / 0.5	2:00 / 0.5

Table 1: Processing times and resulting processing rates of the 3x3 machine model.

Here, λ_m is the mean arrival rate, α is the amplitude of the sine function, and φ indicates a phase shift.

The mean arrival rate λ_m has to be equal or lower than the total processing rate μ to guarantee stable system behaviour with finite buffer levels:

$$\lambda_m \leq \mu \,. \quad (2)$$

For the described 3x3 machine model, the mean arrival rate has to be chosen to:

$$\lambda_m \leq 0.5 \frac{1}{h} \,. \quad (3)$$

Due to a usual workload of about 80 % in real production systems, a mean arrival rate λ_m = 0.4 1/h and amplitude of α = 0.15 1/h are chosen:

$$\lambda(t) = 0.4 + 0.15 \cdot \sin(t + \varphi) \,. \quad (4)$$

The arrival functions for the three product types A, B and C are identical except for the phase shift φ = 1/3 period. This phase shift is chosen to simulate a seasonal varying demand for the three different products. Figure 2 shows the three arrival functions. Here, the arrival rate is plotted against the simulation time for one simulation period.

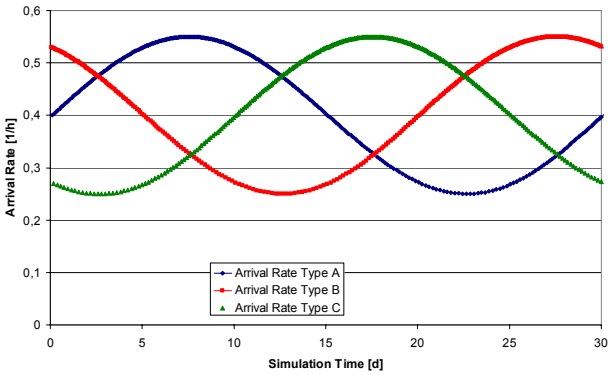

Figure 2: Arrival rate for the three part types.

To analyse the system's performance, the throughput times (TPT) for the three different part types are examined. Figure 3 shows these throughput times. Because of the identical arrival functions for each part type, the time series of the throughput times have the same shape with a phase shift of 1/3 period.

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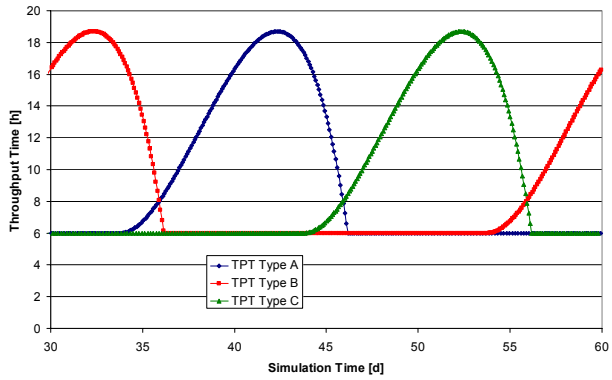

Figure 3: Throughput times for the three different part types in case of conventional planning.

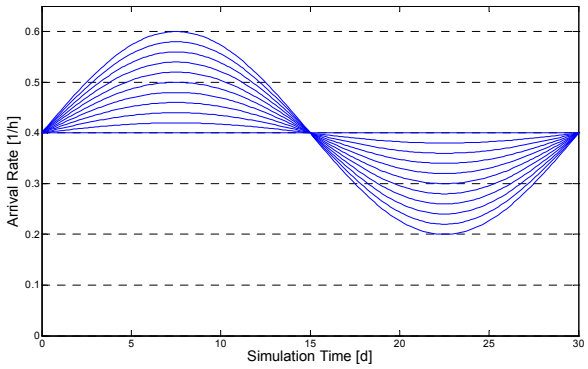

Figure 4: Varying amplitudes of the arrival function for part type A

During the periods of overload, the throughput times rise because the buffer levels at the first stage machines rise and the parts have a higher waiting time before they are processed. When the arrival rate drops below 0.5 1/h, the buffer levels and the waiting times decline until the minimum throughput time of 6 h is reached.

For all three part types the maximum throughput time in this case is 19:48 h and the mean throughput time is 9:55 h with a standard deviation of 5:08 h (see Table 3).

To understand the impact of seasonal demand fluctuations on the system's behaviour, the amplitude of the sinusoidal arrival rate is varied like shown in figure 4. The amplitude rises here from α = 0.0 1/h to α = 0.2 1/h.

The resulting throughput times are shown in figure 5. For amplitudes lower than 0.1 1/h, the throughput time remains constantly 6 h which is the total processing time at all three machines. For amplitudes higher than 0.1 1/h, the temporary overload results in an increased throughput time caused by an additional waiting time in the first buffer. This effect shows the system's inability to react on demand fluctuations. Notice the maximum throughput time of 37:24 h for the amplitude α = 0,2 1/h.

To analyse the robustness of the conventionally planned system, a machine failure at machine M_{21} and a downtime for 12 h is modelled. Due to this single breakdown, the complete production line is blocked for 12 h. The arriving parts pile up in the second buffer and no products leave the line.

Figure 6 shows the effect of this breakdown on the throughput time for product type A. The abrupt rise can be interpreted as system's inability to react to unexpected disturbances and changing constraints.

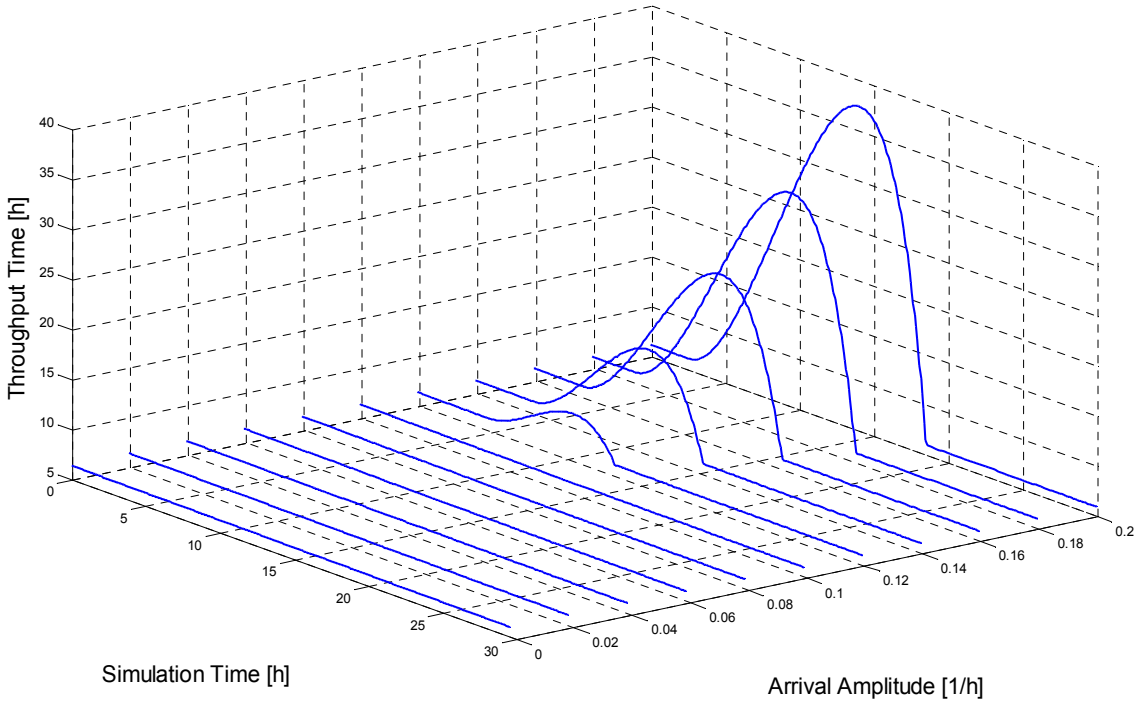

Figure 5: Throughput time of product type A for rising amplitudes in the sinusoidal arrival rate.

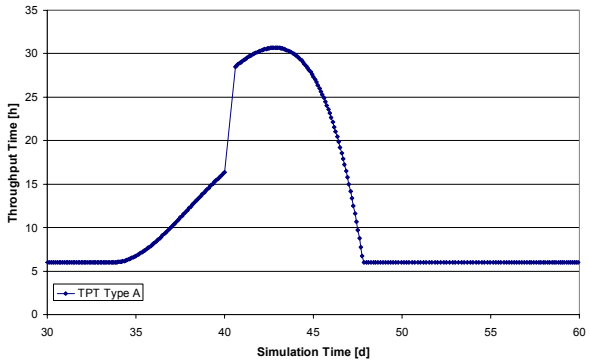

Figure 6: Throughput time for product type A during a breakdown of machine M_{21}.

4.2 Autonomous Control

The second case to be analysed is the autonomous control situation. Here, the parts are autonomous in their decision which machine to choose. They take into account the fact that the processing times are different for each product type. The processing times are on foreign lines higher than on their own line. Table 2 shows the processing times and the resulting processing rates for the three different product types on the three production lines.

Part Type	Processing times [h:min] / Processing rates [1/h] at production line n		
	1	2	3
Type A	2:00 / 0.5	2:30 / 0.4	3:00 / 0.33
Type B	3:00 / 0.33	2:00 / 0.5	2:30 / 0.4
Type C	2:30 / 0.4	3:00 / 0.33	2:00 / 0.5

Table 2: Processing times and resulting processing rates of the 3x3 machine model.

The parts have the lowest processing times on their own line and have higher processing times if they change the line. The decision about changing the line is made by the part itself on the basis of local information about buffer levels, i.e the expected waiting time until processing and the processing time itself. Thereby, the parts take into account that the processing times are higher on foreign lines than on their own. At each production stage the parts compare the future processing times of the parts in the buffers and their own processing time on the respective machine and choose the machine with the minimal time for being processed.

Like the conventionally planned system, the mean arrival rate λ_m has to be equal or lower than the total processing rate μ to guarantee stable system behaviour with finite buffer levels. Unfortunately, the mean arrival rate cannot be determined trivially by equation (2) because of the line switching of the parts i.e. the number of parts that switch the line and the different processing times at different lines.

For description of the relation between arrival rate and processing rate, the workload is defined as:

$$W = \frac{\lambda}{\mu}. \tag{4}$$

where λ is the arrival rate and μ the processing rate. The workload of the machines at the first stage is defined by:

$$W_{11} = \frac{\lambda_1 - (w_{12} + w_{13})}{\mu_{A11}} + \frac{w_{21}}{\mu_{B11}} + \frac{w_{31}}{\mu_{C11}} \tag{5}$$

$$W_{12} = \frac{\lambda_2 - (w_{21} + w_{23})}{\mu_{B12}} + \frac{w_{12}}{\mu_{A12}} + \frac{w_{32}}{\mu_{C12}} \tag{6}$$

$$W_{13} = \frac{\lambda_3 - (w_{31} + w_{32})}{\mu_{C13}} + \frac{w_{13}}{\mu_{A13}} + \frac{w_{23}}{\mu_{B13}} \tag{7}$$

where λ_i is the arrival rate at source i, μ_{Xij} is the corresponding processing rate for the different part types (see Table 2) and w_{ij} is the switching rate from line i to line j.

Because of the interdependencies between the switching rates w_{ij} and the dependencies from the arrival rates λ_i, the workload problem is not analytically solvable. Therefore the stability condition in this case is not trivial to define. Nevertheless, the mean arrival rate still has to be equal or smaller than the processing rate. But due to reduced processing rates, the maximum mean arrival rate is not anymore $\lambda_{m,max}$ = 0.5 1/h.

In high workload situations, the systems total processing rate μ_{total} is a function of the arrival rate because a high arrival amplitude causes line switching and therefore a changing total processing rate.

$$\mu_{total} = f(\lambda(t)) \tag{7}$$

Thus, the stability of the system for different mean arrival rates and amplitudes is tested by analysing the amount of work-in-process (WIP) after a simulation run. If the system reaches the instable area the work-in-process rises to infinity.

The simulation results for different mean arrival rates and different amplitudes are shown in figure 7.

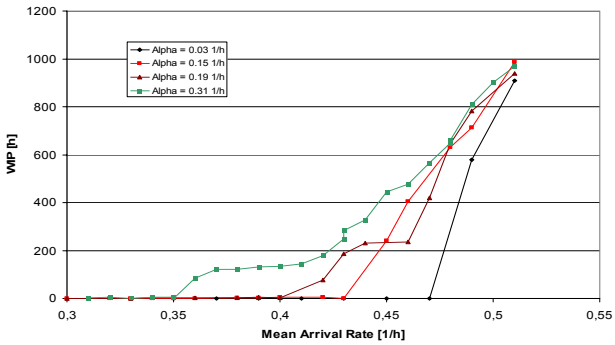

Figure 7: Work-in-process against the mean arrival rate for different amplitudes.

Each point indicates the total work-in-process (WIP) after one simulation run for a certain mean arrival rate. The four different curves denote four different amplitudes. For each curve, a critical mean arrival rate λ_c is observed beyond which the system becomes instable.

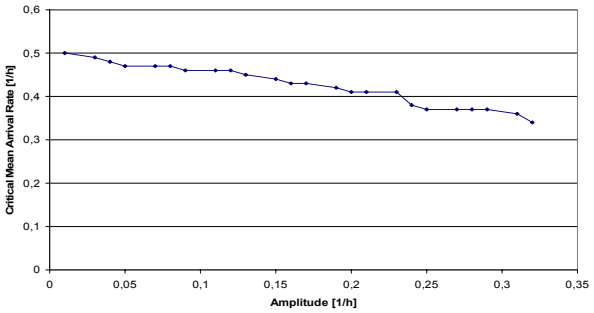

Figure 8: Critical mean arrival rate against the amplitude.

Figure 8 shows these critical arrival rates λ_c for different amplitudes. A linear falling trend between the amplitude and the critical mean arrival rate is observed. This means that in case of autonomous control i.e. the admittance of line switches, the maximum mean arrival rate $\lambda_{m,max}$ depends on the demand variance i.e the amplitude α of the arrival rate.

$$\lambda_{m,\max} = f(\alpha) \tag{8}$$

From the data points plotted in figure 8 equation (9) for the maximum mean arrival rate is extrapolated.

$$\lambda_{m,\max} = -0{,}5 \cdot \alpha + 0{,}5 \tag{9}$$

To analyse the performance of the system the time series of throughput times for the three different product types for a mean arrival rate λ_m = 0.4 1/h with an amplitude α = 0.15 1/h are shown in figure 9. Again identical shaped time series of the throughput times of each lot type are observed but the maximum and the mean throughput times have been significantly reduced in comparison to the conventionally planned system.

Obviously, this effect occurs because in case of work overload the parts switch to other lines even if the processing time is higher there. In this case the maximum throughput time is reduced by 36 % to 12:17 h and the mean throughput time is reduced by 30 % to 6:46 h with a standard deviation of only 1:07 h (see Table 3).

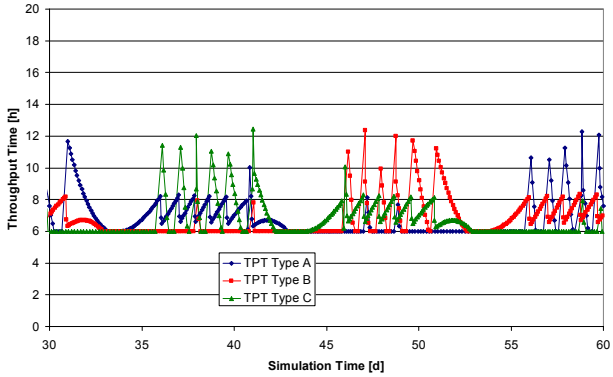

Figure 9: Throughput times for the three different part types in case of autonomous control.

To understand the impact of seasonable demand fluctuations on the system's behaviour, the amplitude of the sinusoidal arrival function with a mean arrival rate λ_m = 0.4 1/h is varied like shown in figure 4. The resulting time series of the throughput time are shown in figure 10.

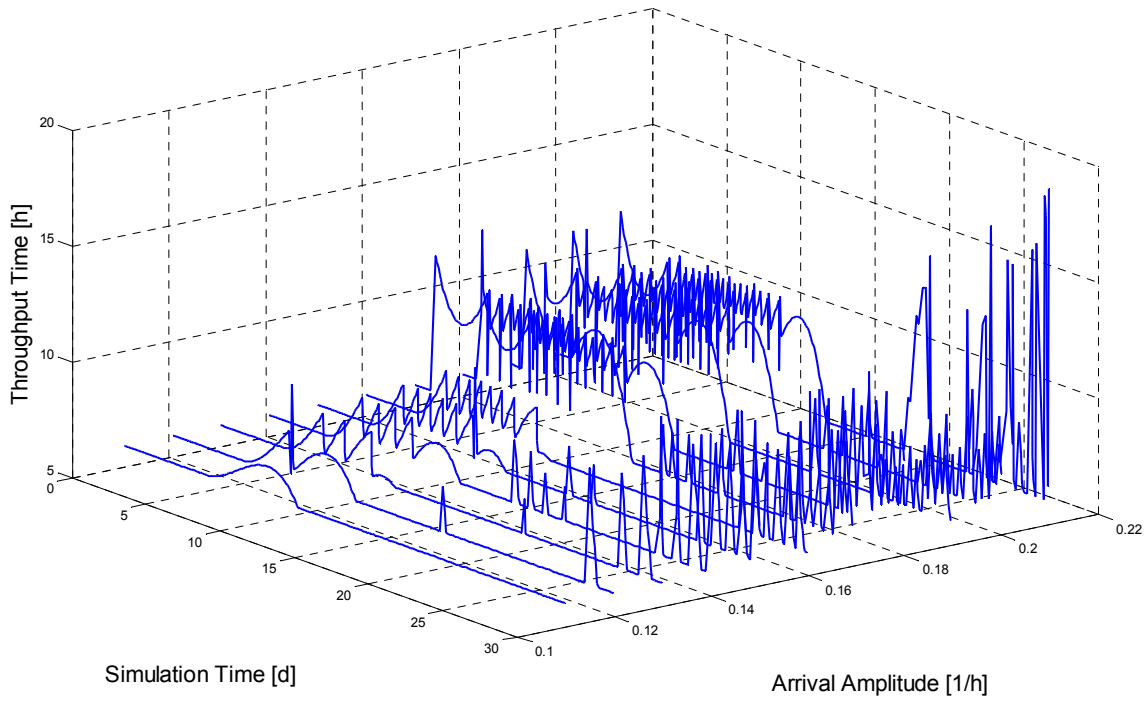

Figure 10: Throughput time of product type A for rising amplitudes in the sinusoidal arrival rate.

The autonomous control effects start at amplitude of 0.1 1/h. The time series show the more complex dynamics, but a significantly reduced throughput time in maximum, mean, and variance. Notice the maximum throughput time of 12:00 h for the amplitude of 0.2 1/h before beginning to destabilise.

In the upper right corner, a beginning destabilisation is observed. For higher amplitudes, the throughput time rises to infinity because of the system's overload (see also figure 8 and equation 9).

To analyse the robustness of the autonomously controlled shop floor, a machine failure at machine M_{21} and a downtime for 12 h is modelled. Figure 8 shows the resulting throughput times for autonomously switching parts.

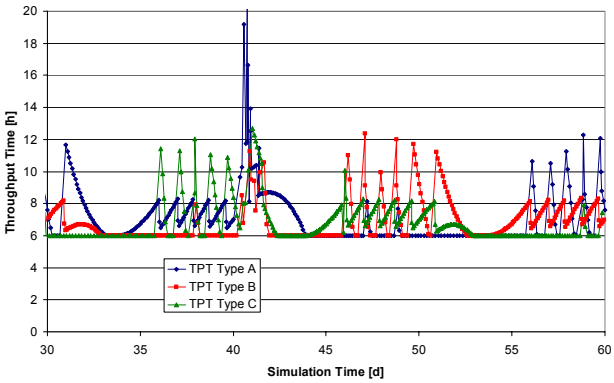

Figure 11: Throughput times for the three part types during a breakdown of machine M_{21}.

One can see a sudden rise of the throughput time of part type A which reaches a maximum of 21:00 h. But this high throughput time is quickly reduced and again the parts are distributed between the lines. In this case the mean throughput time for parts of type A rises to 7:00 h with a standard deviation of 1:34 h (see Table 3) while the mean throughput times for type B rises to 6:55 h respectively to 6:52 h for parts of type C.

	Min TPT [h:min]	Max TPT [h:min]	Mean TPT [h:min]	SDV TPT [h:min]
Conventional planning	6:00	18:42	9:42	4:42
Autonomous control	6:00	12:17	6:46	1:07
Conventional planning and machine failure (only type A)	6:00	30:42	11:23	7:35
Autonomous control and machine failure (only type A)	6:00	21:00	7:00	1:34

Table 3: Performance measures of the 3x3 machine model.

Table 3 summarises the results for a sinusoidal arrival function with a mean arrival rate λ_m = 0.4 1/h and an amplitude α = 0.15 1/h. These results underline the benefits of a autonomous control of shop floor logistics. Although the highest possible workload for the system is reduced, the ability to react autonomously to varying conditions like demand fluctuations or unexpected disturbances like machine failures is extremely improved.

5 SUMMARY AND OUTLOOK

Summarising one can say that by introduction of alternative processing capacities and autonomous control strategies based on local information and local decision-making of intelligent parts, the shop floor can adapt itself to changing work loads and can autonomously react to unexpected disturbances. This motivates further research in this area. In particular it will be interesting to analyse the impact of set up times, dynamic lot sizing and a dynamic capacity control. This will increase the level of autonomy in the system. It will be interesting to investigate which combination of the different autonomous strategies results in what kind of global behaviour. Furthermore the higher level of autonomy will produce a more complex dynamic that could be analysed using tools from the field of nonlinear dynamics.

6 ACKNOWLEDGMENTS

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