Dynamics of Autonomous Control in Production Logistics

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Abstract
The paper gives an overview of the modeling and analysis of autonomous control strategies for production logistics. A universal shop floor model, built with Vensim DSS, is introduced. AC strategies are discussed and implemented. The particularities of modeling a production logistic scenario are presented. Based on the simulation results the logistics performance as well as the influence on the system's behavior is assessed. The main focus lies on the comparison of the effects of the different autonomous control strategies on the logistics performance of the system and its behavior. To achieve this goal, sensitivity analysis is used to compare the robustness of the logistic system while interchanging the control strategies.

1. Introduction

Production planning and control (PPC) systems have to cope with rising complexity and dynamics. Conventional PPC methods cannot handle unpredictable events and disturbances in a satisfactory manner because in practice the complexity of centralized architectures tends to grow rapidly with size, resulting in rapid deterioration of fault tolerance, adaptability and flexibility [1]. One approach to overcome these difficulties is to develop decentralized systems with autonomous control methods to reduce the complexity that has to be taken into account for rendering decisions [2].

Autonomous control is defined by: "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" [3]. In the context of engineering science, this global definition is adapted: "Autonomous Control in logistic systems is characterized by the ability of logistic objects to process information, to render and to execute decisions on their own" [3]. Thus, decentralized and autonomous control strategies incorporate autonomous elements that are able to render decisions by themselves using distributed local information. Consequently, 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.

Recent developments in information and communication technology, such as radio frequency identification (RFID), wireless communication networks etc., enable intelligent and autonomous logistics object to communicate with each other and with their resources and to process the acquired information. Combining the autonomous control approach with the developments in information and communication technology may lead to a coalescence of material flow and information flow and enable the logistic objects to manage and control its manufacturing process autonomously [2].

Modeling and benchmarking autonomous control strategies requires dynamic models. Furthermore, one has to consider both, the local decision-making processes as well as the global behavior of the system. The interactions and interdependencies between local and global behavior are called Micro-Macro-Link, which is not trivial to describe and analyze. In a colony of ants for example a single ant has no idea about the whole colony. Its actions are based on a few simple rules. On the other hand, 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-organization is a so-called emergent behavior of a complex dynamic system and is not derivable from single characteristics [4, 5].

Several continuous system dynamics models, built with Vensim DSS, are presented in the following. They describe exemplary scenarios of a shop floor. The term continuous denotes the continuous material flow, which differs from the flow of discrete parts in e.g. a discrete event simulation model. In literature, continuous flow models of production systems are often called hybrid models [6, 7]. That means the material flow is modeled as continuous flow which is controlled by discrete actions. This discrete control is typical for production systems. In a second step, autonomous control strategies are developed and implemented. The main goals of this paper are (1) to give an overview of modeling of autonomous control strategies for production logistics scenarios and (2) to compare the effects of the different PPC strategies on the logistics performance of the system and its behavior and to find answers to the question: How can different PPC strategies cope with different levels of market dynamics, i.e. fluctuating demand? To achieve this goal, sensitivity analysis is used to compare the robustness of the logistic system while interchanging the control strategies.

2. Exemplary Scenarios

The considered exemplary scenario is a matrix-like flow-line manufacturing system producing k different products at the same time. Each of the products has to undergo m production stages. For each of these production stages there are n parallel production lines available. Therefore, the shop floor consists of mxn machines. The raw materials for each product enter the system via sources and the final products leave the system via drains. The production lines are coupled at every stage and every line is able to process every type of product within a certain stage. At each production stage a part has to make an autonomous decision to which of the lines to go to in the next stage. Each machine has an input buffer in front, containing items of the k product types. The arrival rates are chosen to simulate a varying seasonal demand for the different product types. Thus, the arrival functions for the three product types are defined as sine functions. They are identical except for a phase shift of $1/k$ period (for the topology, see Figure 1 and cf. [8, 9]). This scenario was chosen because of its general and universal character, it can be applied to the majority of real world shop floor configurations.

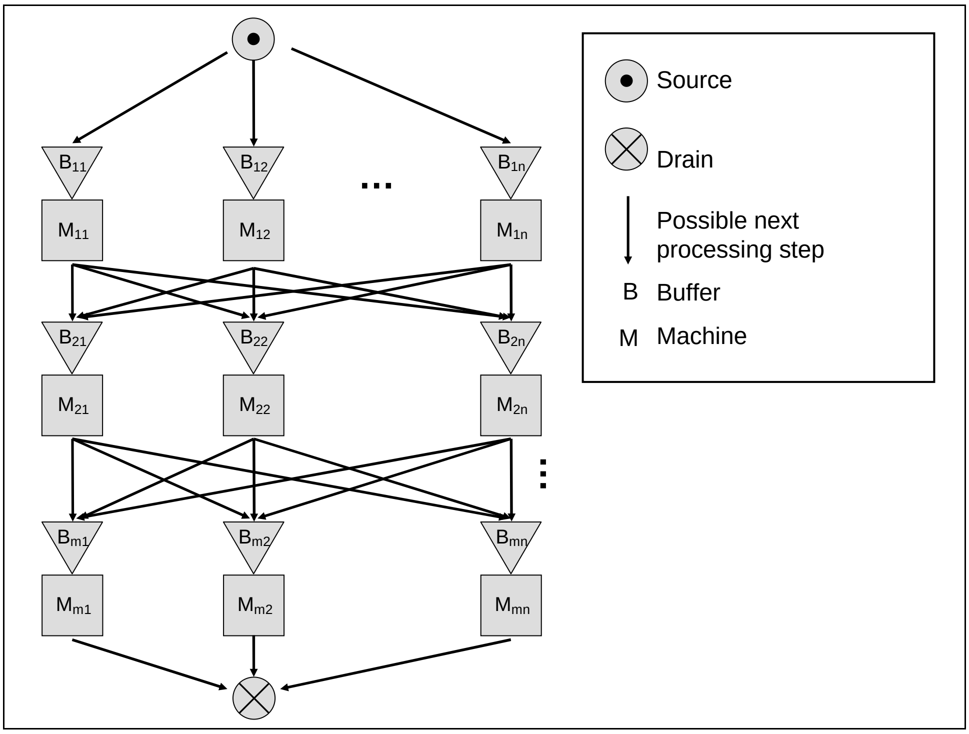

Figure 1: Universal mxn shop floor scenario.

Additionally, it is assumed that different product lines are more suitable for certain products. In other words: A part is punished when it decides to switch production lines. This can be done either by different setup times or by different processing times on the different machines. Whereas setup times are very common, different processing times without setup times can be found for example in the food processing industry, where e.g. an enwrapping machine can enwrap different products in different times without any setups. This is different from scenarios where setup times are understood as a punishment only for the first part of the new type that switches production lines. In this context, the machines' service rule for the different product types is important, e.g. it may be first in - first out (FIFO) for scenarios with different processing times and without setup times and has to be adapted to a rule that considers the current setup status in scenarios with setup times.

In the following, different autonomous control strategies for these scenarios with both, different processing times and different setup times will be presented. To analyze the system's behavior the logistics performance is benchmarked. Three exemplary criteria of logistics performance in production systems are presented: the throughput times of parts, the buffer levels at one production steps and the inventory levels (aggregated buffer levels).

3. Autonomous control strategies

Different autonomous control strategies can be distinguished by the information they use in the decision making process: rational strategies may rely on information about the current situation and a prediction of a future situation of the system (expected values) or on information about how good alternatives had been in the past (experience of the predecessors) or on both.

The queue length estimator

The queue length estimator (QLE) [8, 9] is an autonomous control strategy that lets a part compare actual buffer levels of the different alternatives (all parallel machines) that are able to perform its next production step. In this case, the buffer levels are calculated as the sum of the estimated processing times of the waiting parts in the respective buffer on the respective machine plus its own expected processing time. When a part has to render the decision about its next processing step it compares the current buffer levels, i.e. the estimated waiting time until processing, and chooses the buffer with the shortest waiting time. Thus, the QLE uses the available information to predict the systems future state. The QLE can be used for scenarios with different processing times as well as scenarios with setup times.

The pheromone-based autonomous control strategy

The pheromone-based autonomous control strategy [10, 11, 12] uses data from past events. Every time a part leaves a machine, i.e. after each processing step, the part leaves information about the duration of its processing and waiting time at the respective machine. The following parts use these data to render their decisions. Thus, the parts' decisions are based on backward propagated information about the throughput times of finished parts for different routes. Routes with shorter throughput times attract parts to use these routes again. This process can be compared to ants leaving pheromones on their way to communicate with following ants. As in other pheromone concepts [13, 14], the communication takes place indirectly by changing the environment. The parts have to be able to access updated information about throughput time only. Thus, this pheromone-based autonomous control strategy differs from approaches from ant colony optimization (ACO, e.g. [13]) since there is no self-reinforcing guided search process for optimal solutions. The pheromone concentration depends on the evaporation of the pheromone and on the time previous parts had to spend waiting in the buffer in addition to the processing time on the respective machine as well as the throughput time. Clearly the fine-tuning of the evaporation constant for the pheromone is crucial. The pheromone-based autonomous control strategy can be used for scenarios with different processing times. However, in a pheromone-based concept, setup times are somewhat hard to handle because predecessors' decisions have influence on successors, which is ordinary not communicated by the pheromone. This dilemma can be solved by the introduction of a correction term for the pheromone concentration [12].

Mixed strategy

The QLE and the pheromone-based autonomous control strategy can be combined to a mixed strategy [12] that incorporates a weighted combination of the prediction of the future state of the system and the experience of predecessors. This mixed strategy can be used for scenarios with different processing times and different setup times.

4. Modelling details and simulation results

To handle the complexity, the simulation model is reduced to 3x3 machines producing 3 different products. The model is build with Vensim DSS as sequences of buffer-machine-systems. The buffer-machine-systems are modeled in a way that only a complete part may enter a machine and only if the machine is empty. The discretized fluxes of parts are modeled as flows between box-variables that represent the buffers. The parts' autonomous decisions are implemented with the help of branched outflux and multi-nested if-then-else clauses.

One simulation period is set to 30 days. The arrival functions for the three product types are defined as sine functions as a representation of the seasonal varying market demand. They are identical except for a phase shift $\varphi = 1/3$ period. Due to a usual workload of about 80 % in real production systems, a mean arrival rate $8_m = 0.4\ 1/h$ and an amplitude of the sine functions of $\forall = 0.15\ 1/h$ are chosen, meaning that on average every 2:24 h a new part of product type A, B and C respectively arrives to the system.

Scenario 1 – Without line switching with different processing times and without setups

It is assumed that each machine at each stage has different processing times for each product. Table 1 shows the different processing times for the different product types and production lines.

Product type	Processing times [h:min] at production line		
	1	2	3
Type A	2:00	2:30	3:00
Type B	3:00	2:00	2:30
Type C	2:30	3:00	2:00

Table 1: Processing times of the 3x3 machines model.

When prohibiting line switching, each part is directed to its preferred production line. This can be interpreted as a central and preplanned control in PPC, depicting a scenario, in which the seasonal varying demand could not be forecasted.

To analyze the logistics performance of this system, the throughput times (TPT) for the three different part types are examined. They are calculated in real-time with the help of Little's Law [8]. Figure 2 shows the throughput times for this scenario (maximum throughput time 19:48 h and the mean throughput time is 9:55 h with a standard deviation of 5:08 h). As could be expected, the parts just pile up in the buffers during periods of overload. 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. 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.

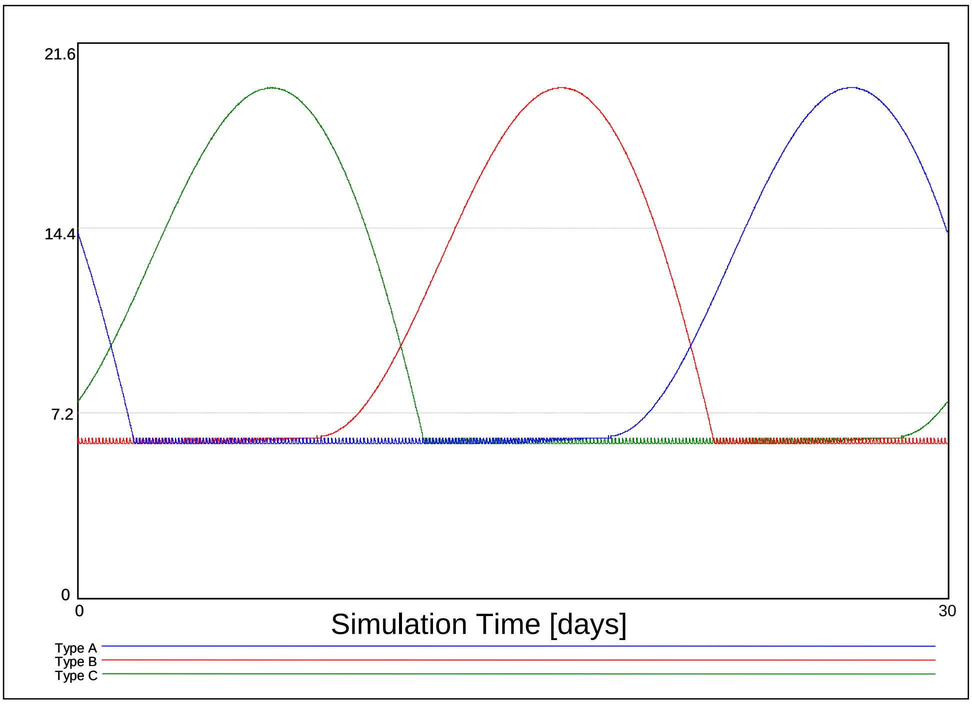

Figure 2: Throughput times for the three different part types in case of preplanning and without setup times but with different processing times.

Scenario 2 – QLE in a scenario with different processing times and without setups

Each machine at each stage has different processing times for each product (see Table 1). The implementation of the queue length estimator as an autonomous control strategy is pretty straightforward. The already mentioned multi-nested if-then-else clauses compare the buffer levels of the different machines and direct the flux of parts to the buffers with the lowest expected waiting times. Again, the throughput times for the three different part types are examined. Figure 3 shows the throughput times for this scenario. It can be seen that the logistics performance is significantly better as in scenario 1 (the maximum throughput time is reduced by 26 % to 14:42 h and the mean throughput time by 18 % to 8:07 h with a standard deviation of 2:14 h).

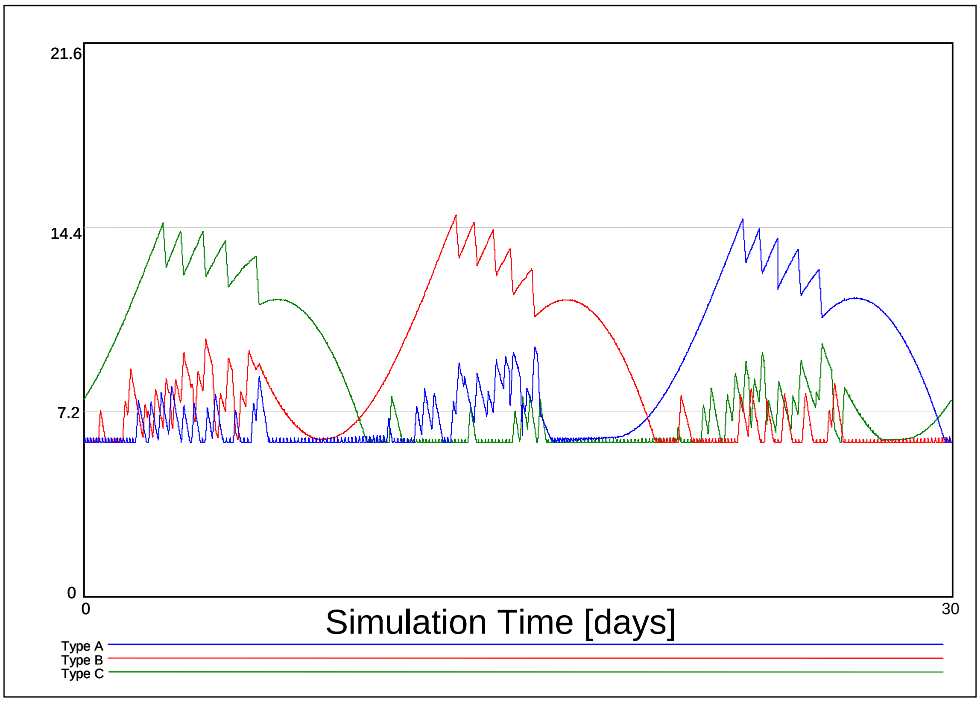

Figure 3: Throughput times for the three different part types with QLE in the case without setup times but with different processing times.

Scenario 3 – Pheromone-based autonomous control strategy in a scenario with different processing times and without setups

In this scenario it is again assumed that each machine at each stage has different processing times for each product (see Table 1). To implement the pheromone-based autonomous control strategy a new box variable for each product type at each machine buffer system is introduced. This box variable contains the pheromone concentration. It is updated by the actual throughput time plus the waiting time of every part that has just been processed. Additionally, the concentration is diminished by an 'evaporation constant', which ensures an exponential decay of the amount of pheromone – the equivalent to an evaporation process.

Here, one advantage of Vensim DSS can be seen: Discrete event simulators (as for example eMPlant) ardinary may not handle the evaporation-process between two events properly. Thus, with a discrete event simulator, one would be forced to rely on a moving average of the last parts to implement a pheromone-based approach [10]. The concentration of the pheromone depends on the evaporation of the pheromone and on the time previous parts had to spend waiting in the buffer in addition to the processing time on the respective machine as well as the throughput time. Randomly, the pheromone concentration at one buffer machine system is 'manually' increased to manipulate the next part's decision to use a different way than that one with the highest pheromone concentration. This is to model the equivalent to the 'random-walk of ants' – it is necessity to try different ways to find possibly shorter ways as well.

Thus, the pheromone concentration update algorithm works as follows: Let $P_{mnk}(t)$ denote the pheromone concentration for machine mn at time t, E_{mnk} the evaporation constant ($0 < E_{mnk} << 1$) for product type k at machine mn, β_{mnk} a (constant) adjustment factor for the pheromone concentration update for product type k at machine mn and $TPT_{mnk}(t)$ the actual throughput time for product type k at machine mn. Then the pheromone updating process is given by:

$$P_{mnk}(t) = P_{mnk}(t) - P_{mnk}(t-1) * E_{mnk} + \begin{cases} \beta_{mnk} * TPT_{mnk}(t), if \ \text{'machine has completed its job'} = true \\ 0, else \end{cases} \tag{1}$$

To evaluate the system's performance and to show, how another criterion for the logistics performance can be analyzed, the buffer levels for the three buffers of the first production step are examined (maximum 8.26 pieces, mean buffer level is 3 pieces with a standard deviation of 3.05 pieces cf. Figure 4).

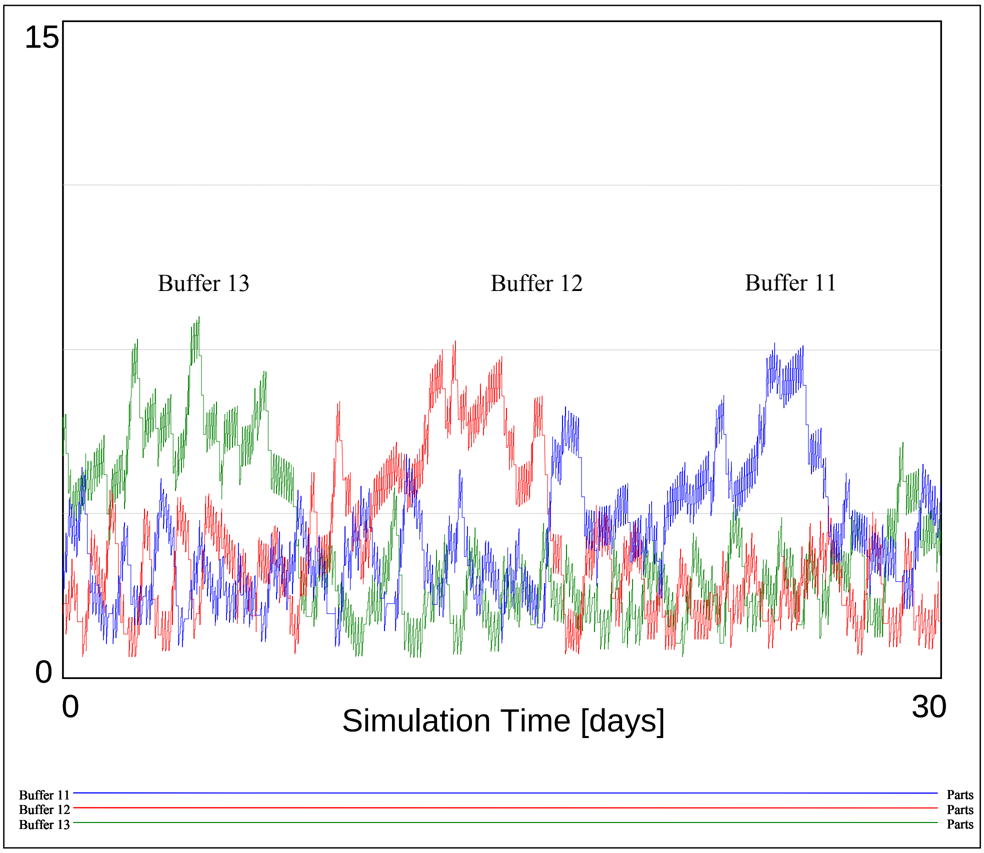

Figure 4: Aggregate buffer levels of the first production step with pheromone-based autonomous control in the case without setup times but with different processing times.

Scenario 4a – Pheromone-based autonomous control strategy in a scenario with setup times

Now it is assumed that the processing times for each product are the same: 120 minutes and that set-up times have to be taken into account (see Table 2).

Set-up times [min]	Machine M_{m1}	M_{m2}	M_{m3}
A -> B	30	10	60
A -> C	60	30	10
B -> A	10	60	30
B -> C	60	30	10
C -> A	10	60	30
C -> B	30	10	60

Table 2: Setup times of the 3x3 machines model.

When implementing the pheromone-concept as in scenario 3 (cf. Equation 1), it does not perform in a satisfactory manner (maximum inventory is 13.86 pieces and the mean inventory is 8.65 pieces with a standard deviation of 6.11 pieces cf. Figure 5). Here, the inventory was chosen as a criterion for the logistics performance of the system. It can be calculated by the aggregation of the buffer levels at, e.g. the first production step.

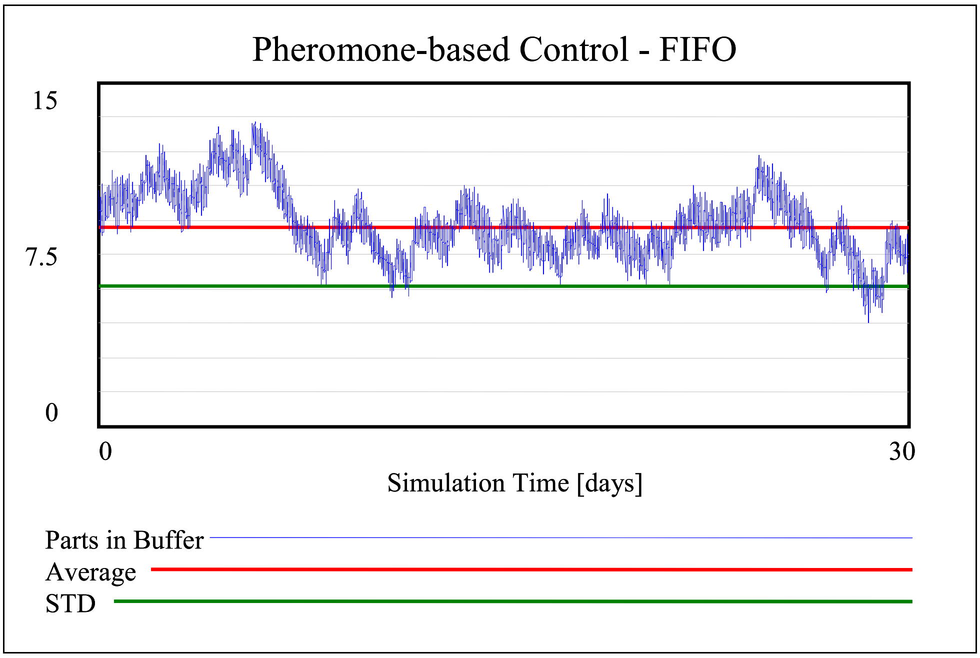

Figure 5: Aggregate buffer levels of the first production step with pheromone-based autonomous control in a scenario with setup times.

Because of two reasons this performance seems to be improvable: The pheromone concentration does not include information about the set-up status of the machine and, a part's decision can be both, good or bad, depending on how many set-ups the machine has to perform before the part can be processed. The second reason is not included in the pheromone concentration either. Thus, the machines' service rule has to be improved and a correction term for the pheromone concentration has to be implemented.

Scenario 4b – Improved pheromone-based autonomous control strategy with a correction term and with adapted machines' service rule in a scenario with setup times

In scenario 4b the setup does not change but the pheromone-based autonomous control strategy is adapted and the machines' service rule is improved. A service rule, which enables the machines to select autonomously, which part to process next, is implemented. This can be achieved by letting the machines try first to empty the buffer of parts of the same product type.

The update of the pheromone concentration works as described in scenario 3 but additionally, a correction term is introduced. This correction term includes information about the product type a machine is setup to after a part has been processed. This can not be done by simply leaving a higher amount of the pheromone because this additional information should effect a direct successor's decision only. A higher pheromone quantity would evaporate over time according to the evaporation constant leading to bad information for the next but ones' decisions. Thus, the correction term consists of an increasing of the pheromone concentration but with a higher evaporation constant. The pheromone update algorithm works as follows: Let $CT_{mnk}(t)$ denote the value of the correction term for product type k at machine mn at time t, δ_{mnk} a constant adjusted to the execution time for product type k at machine mn, EC_{mnk} the evaporation constant for the correction term (1 > EC >> E) for product type k at machine mn and $set\text{-}up\_status_{mn}(t)$ the status the machine mn is actually set-up to. Then, the pheromone concentration with correction term $P\_cor_{mnk}(t)$ consists of the pheromone part $P\_part_{mnk}(t)$ and the correction term part $CT_{mnk}(t)$:

$$
\begin{aligned}
&P\_cor_{mnk}(t) = P\_part_{mnk}(t) + CT_{mnk}(t)\\
&with\\
&P\_part_{mnk}(t) = P\_part_{mnk}(t) - P\_part_{mnk}(t-1) * E_{mnk}\\
&+\begin{cases} \beta_{mnk} * TPT_{mnk}(t), if \ \ 'machine\ has\ completed\ its\ job' = true \\ \qquad\qquad\qquad\qquad 0, else \end{cases}\\
&and\\
&CT_{mnk}(t) = CT_{mnk}(t) - CT_{mnk}(t-1) * EC_{mnk}\\
&+\begin{cases} \delta_{mnk}, if \ \ set-up\_status_{mnk}(t) = k \\ \qquad\qquad 0, else \end{cases}
\end{aligned}
\tag{2}
$$

Adjusting the higher evaporation constant for the correction term EC_{mnk} to the execution time (processing time plus set-up time) of the next part on a particular machine, the improved pheromone-based autonomous control strategy should performs better. It can be implemented by a second box variable that acts like the first box variable as described in scenario 3. The circular multi-nested if-then-else clauses that regulate the handing-over process to the chosen buffer have to sum up the pheromone concentration and the concentration of the correction term. Figure 6 shows the aggregate buffer levels of the first production step.

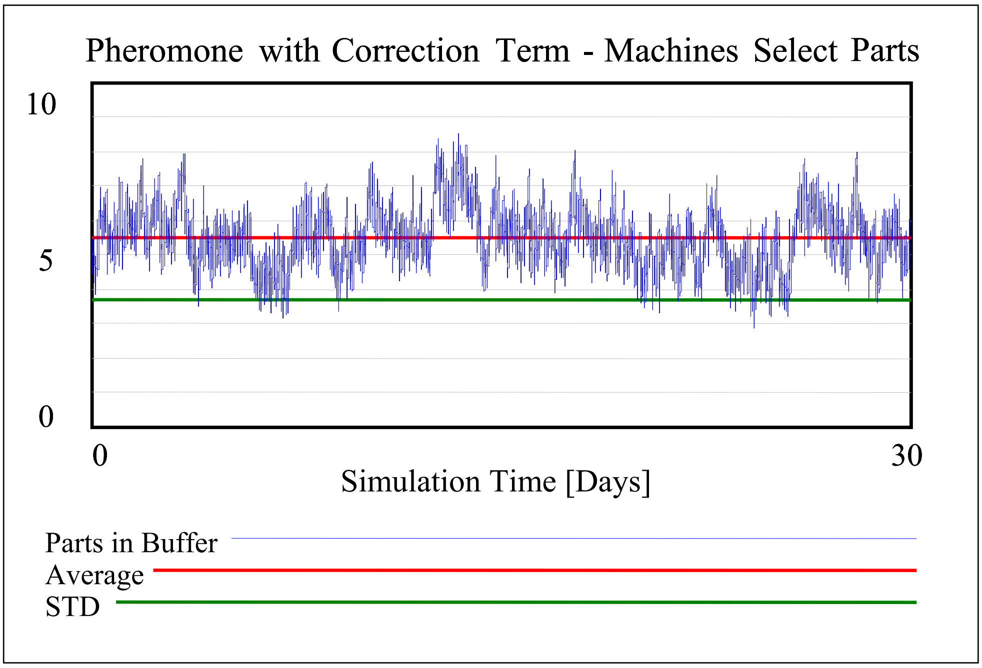

Figure 6: Inventory of the first production step with an improved pheromone-based autonomous control strategy with a correction term and with adapted machines' service rule.

As can be seen, the performance is improved compared to scenario 4a. Compared to the pheromone strategy without correction term and without adapted machines' service rule (cf. Scenario 4a) the maximum buffer level is reduced to 8.55, the mean buffer level to 5.51 and the standard deviation to 3.67 pieces.

Scenario 4c – Mixed strategy in a scenario with setup times

In scenario 4c the setup does not change but a different and more sophisticated autonomous control strategy is implemented. The queue length estimator strategy, as it was shown in scenario 2 is combined with the improved pheromone-based autonomous control strategy with a correction term and with adapted machines' service rule from scenario 4b (cf. Equation 2). The result is a mixed autonomous control strategy that incorporates a weighted combination of the prediction of the future state of the system and the experience of predecessors. Both methods have shown their performance capabilities in different scenarios [8, 9, 10, 11]. On the other hand, their degree of logistic goals achieved differs in scenarios with rising structural complexity. The pheromone strategy shows a diminishing degree of logistic goals achieved when the structural complexity rises. The queue length estimator method's degree of logistic goals achieved is hardly affected by rising structural complexity [15]. Thus, the combination of the two strategies is promising. It is implemented by a 0.5:0.5 weighted calculation by the circular multi-nested if-then-else clauses. The logistics performance of this mixed autonomous control strategy in terms of aggregated buffer levels can be seen in Figure 7.

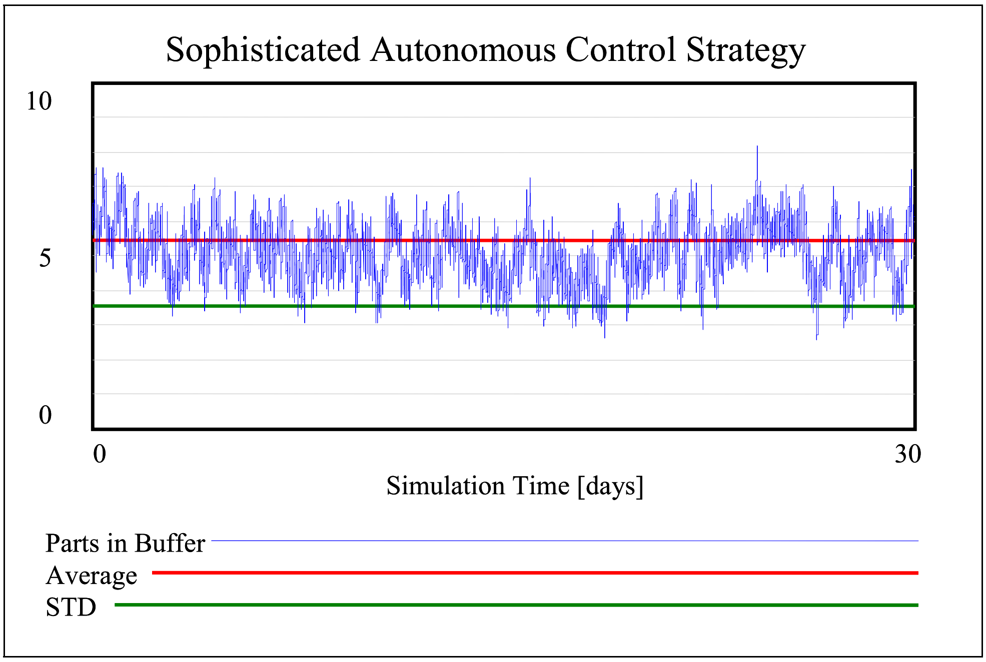

Figure 7: Aggregate buffer levels of the first production step with mixed autonomous control strategy in a scenario with setup times.

The performance of this new autonomous control strategy is excellent. The maximum buffer level is reduced to 8.21 and the mean buffer level to 5.44 pieces with a standard deviation of only 3.55 pieces.

Comparing the AC-strategies' ability to cope with market dynamics

The ability of PPC strategies to cope with changing market dynamics, as for example demand fluctuations, is of high importance for manufacturing companies. In order to analyze the behavior of the AC strategy compared with a traditional PPC strategy, a sensitivity analysis is used. This allows comparing the robustness of the logistic systems also.

For the demand fluctuations, the arrival functions for the three product types have to be altered. The sinusoidal character as well as the phase shift $\varphi = 1/3$ period will be maintained but the amplitude of the sine functions $\forall = 36$ will become subject to multivariate sensitivity analysis and is set to vary between 20 and 52. This means that the systems are analyzed with a very high level of utilization as well – a fact that will lead to a significant rise of the throughput times. Thus, the average throughput times of scenario 1 (central and preplanned control in PPC) and scenario 3 (autonomous control with a pheromone-based approach) are compared. Figure 8 shows the results of the sensitivity analysis of the average throughput time of the traditional PPC strategy with separate lines and Figure 9 the results of the sensitivity analysis of the average throughput time of the pheromone-based AC strategy.

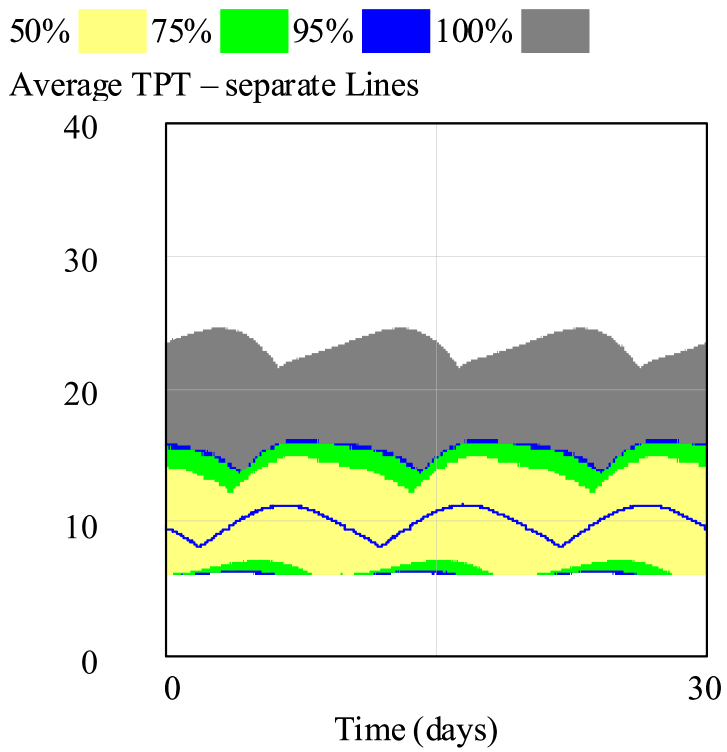

Figure 8: Sensitivity analysis of average TPT of a traditional PPC strategy.

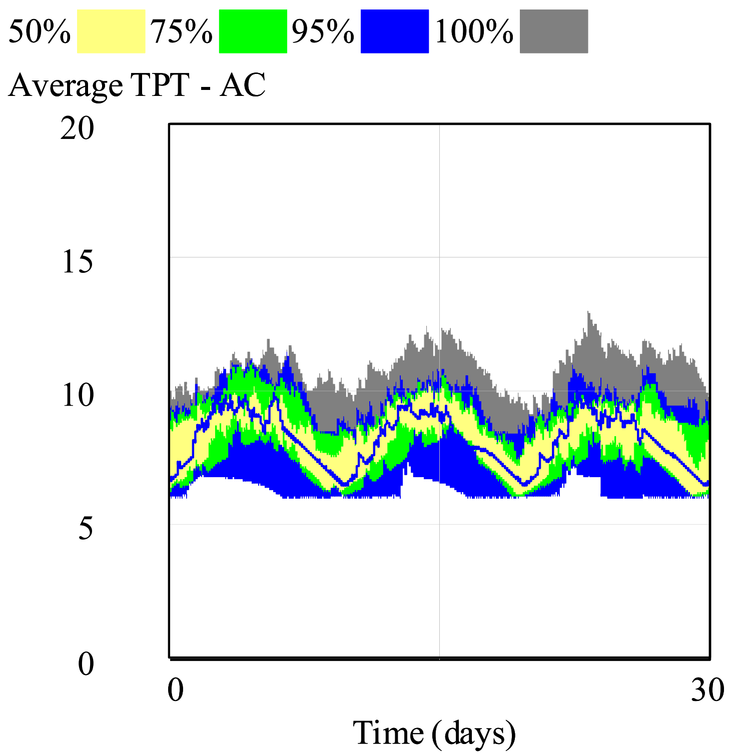

Figure 9: Sensitivity analysis of average TPT of a pheromone-based AC strategy.

Comparing the results it comes immediately to mind that the AC strategy is not only better as far as logistics performance is concerned but it is more robust against dynamic market changes as well. Additionally, it can be seen that the qualitative behavior of the traditional PPC strategy (cf. the sinusoidal character of the fluctuations of throughput times) does not change if demand and thus the utilization changes – here, the AC strategy outperforms the traditional strategy.

5. Conclusions

It was shown how different autonomous control strategies can be modeled and implemented with the help of system dynamics. A general and universal scenario of a shop floor with and without setup times as well as with and without different processing times has been presented. A traditional and several autonomous control strategies have been presented. Modeling details, i.e. the machines' service rule, the equivalent of an autonomous decision, the evaporating pheromone concentration, the implementation of the necessary correction term to the pheromone concentration in scenarios with different setup times to include information about the set-up status of the machine in the pheromone etc. were explained. It turned out that system dynamics offers advantages compared to discrete event simulation especially in modeling the evaporation of the pheromone concentration.
Aditionally, the ability to cope with changing complexity of two different control methods, i.e. a traditional PPC strategy and an autonomous control approach, has been compared. With the help of sensitivity analysis it was shown, that autonomous control strategies can be more robust against market dynamics like demand fluctuations.

6. References

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