Chapter 9
Logistic Systems with Multiple Autonomous Control Strategies

Bernd Scholz-Reiter, Michael Görges, and Thomas Jagalski

9.1 Introduction

Production planning and control (PPC) systems have to cope with rising complexity and dynamics that arise from a higher demand for individualized goods, short delivery times, a strict adherence to due dates and internal unexpected events, e.g. machine breakdowns or rush orders. Conventional production planning and control 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 [8]. 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 [13].

Recent developments in information and communication technology, such as radio frequency identification (RFID), wireless communication networks etc., enable intelligent and autonomous logistic objects 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 their manufacturing process autonomously [13].

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

B. Scholz-Reiter (✉), M. Görges, and T. Jagalski
Department of Planning and Control of Production Systems, BIBA,
University of Bremen, Germany
e-mail: bsr@biba.uni-bremen.de

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nests, to find shortest paths between food and nest etc. [9]. This self-organization is a so-called emergent behavior of a complex dynamic system and is not derivable from single characteristics [20].

Previous studies showed the effectiveness of autonomous control for scheduling tasks (e.g. [2, 14–17]) but so far there is no systematical analysis of autonomous machine rules for buffer clearance. This paper addresses the implementation of autonomous control as a service rule within a generic scenario of a flexible flow shop with a pheromone-based scheduling. Its main goal is to show that multiple autonomous control strategies within one logistic system – although it is possible to design and implement them – may lead to non-desired behavior and bad overall logistic performance. To achieve this goal the contribution is structured as follows: Sect. 9.2 offers an overview of autonomous control for scheduling tasks in production logistics. In Sect. 9.3 a generic exemplary scenario of a flexible flow shop, its modeling details as well as the chosen autonomous control strategy, i.e. a pheromone-based scheduling heuristic, are presented. Section 9.4 describes the design of two autonomous service rules and evaluates the simulation results in comparison to FIFO service rule, showing, that multiple autonomous control strategies within one logistic system may lead to a dilemma. Section 9.5 shows how to solve the dilemma with the help of a simple non-autonomous service rule and evaluates on the necessity of strictly local information for autonomous control by presenting a correction term to the pheromone-based scheduling. Section 9.6 summarizes the results and offers an outlook on future research.

9.2 Autonomous Control for Flexible Flow Shop Scheduling

The main goal of flexible flow shop scheduling is to sequence and assign a set of jobs to a set of production resources in an optimal manner [1]. However, for most instances of this problem class optimal solutions cannot be found within an appropriate time, because these problems are usually NP complete [7, 12]. Instead of finding optimal solutions, different heuristics, e.g. autonomous control strategies, have been developed to derive acceptable solutions. 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' [20]. 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' [20]. Autonomous control aims at increasing robustness and performance of logistic systems [21]. Thus, autonomous control strategies incorporate 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 – and all that as local as possible. On the other hand, the logistic structure has to provide distributed information about local states and different alternatives to both enable decisions in general and to enable sophisticated decisions that offer an acceptable solution.

According to a classification, introduced by Windt and Becker (2009), these local information methods can be grouped as follows: rational strategies, bounded rational strategies and combined strategies [22]. This classification is based on the underlying decision mechanisms used by the different autonomous control methods. Rational strategies utilize rational measures for decision making. Bio-analogous control strategies belong to the group of bounded rational strategies. They aim at transferring fundamental mechanisms of biologic self-organizing systems to autonomous decision making methods. Thus, autonomous control 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. One group of autonomous control strategies that rely on experience of predecessors are bio-analogous control strategies. In literature one can find several attempts to explain the emergent behavior of large scale structures in biological systems. Camazine et al. (2001) offer an overview and some case studies of self-organization in biological systems. The case studies comprise social insects, slime moulds, bacteria, bark beetles, fireflies and fish [5]. According to the authors biological self-organization can be found in group-level behavior that arises in most cases from local individual actions that are influenced by the actions of neighbors or predecessors and in structures that are build conjointly by individuals. Colonies of social insects, e.g. ants or honey bees, show an impressive behavior, which has been classified as Swarm-Intelligence [5]. The individuals follow simple rules that allow solving complex problems beyond the capabilities of single group members. These colonies are characterized by adaptiveness, robustness and self-organization [5]. Several of these rational and biologically inspired autonomous control strategies have been applied to flexible flow shop problems, e.g. the queue length estimator, the pheromone-based control strategy, the honey bee method and mixed strategies.

The queue length estimator (QLE) is an autonomous control strategy that enacts a part to compare actual buffer levels of different alternatives (all parallel machines) that are able to perform its next production step [14]. 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 set-up times.

The pheromone-based autonomous control strategy [2] utilizes 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 in form of an artificial pheromone. 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 (e.g. [3, 10]), 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 (e.g. ACO [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 artificial pheromone is crucial. The pheromone-based autonomous control strategy can be used for scenarios with different processing times. However, in a pheromone-based concept, set-up times are somewhat hard to handle because predecessors' decisions have influence on successors, which is ordinary not communicated by the pheromone. This can be solved by the introduction of a correction term for the pheromone concentration [15].

The honey bee concept has been adapted to flexible flow shop scheduling problems as well [16]. It mimics the food foraging behavior of honey bees, which is slightly different compared to the pheromone concept. Bees that are aware of a food source can advertise the source in order to recruit nest mates by performing a 'waggle dance'. With the help of the dance, the bee conveys information about the known food source to the 'onlooking' bees, i.e. its general direction, distance, and quality [4]. The length of such a dance is proportional to source quality [18]. In a flexible flow shop scheduling scenario a part advertises a good way for following parts after each processing step and the better the alternative is, e.g. the shorter the throughput time was, the longer the advertisement should be. A homecoming collecting bee evaluates the food source by means of the ratio of energy consumption to the energy conveyed to the hive in form of sugar concentration. The better the individual evaluation of the food source quality is the more dance runs the bee will perform [18, 19]. Thus, the more runs the dance has, the longer the advertisement takes and the more unemployed bees can watch it and are attracted to the best food sources. This is different from the pheromone concept because a single ant does no evaluation at all. When transforming the honey bee concept to a flexible flow shop scheduling scenario one would implement this individual evaluation process as well. Thus, the advertising of a good alternative is not decreased by an exponential decay as it is in a pheromone concept but according to the individual evaluation and decision on the number of waggle dances.

The different autonomous control strategies can be combined to a mixed strategy that incorporates a weighted combination of the prediction of the future state of the system and the experience of predecessors (e.g. QLE and the pheromone-based autonomous control strategy, [15]).

So far there is no systematical analysis of autonomous machine rules for buffer clearance. In order to analyze the behavior of a logistic system with multiple autonomous control strategies for scheduling and buffer clearance, a generic scenario of a flexible flow shop with set-up times was established and the pheromone-based autonomous scheduling method was chosen.

9.3 Exemplary Scenario – Modeling Details

The considered exemplary scenario is a matrix-like flow-line manufacturing system producing k different product types 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 $m \times n$ 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. Switching product types requires a set-up. 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 as Fig. 9.1 shows [14]. This scenario was chosen because of its generic and universal character, it can be applied to the majority of real world flexible flow shop configurations.

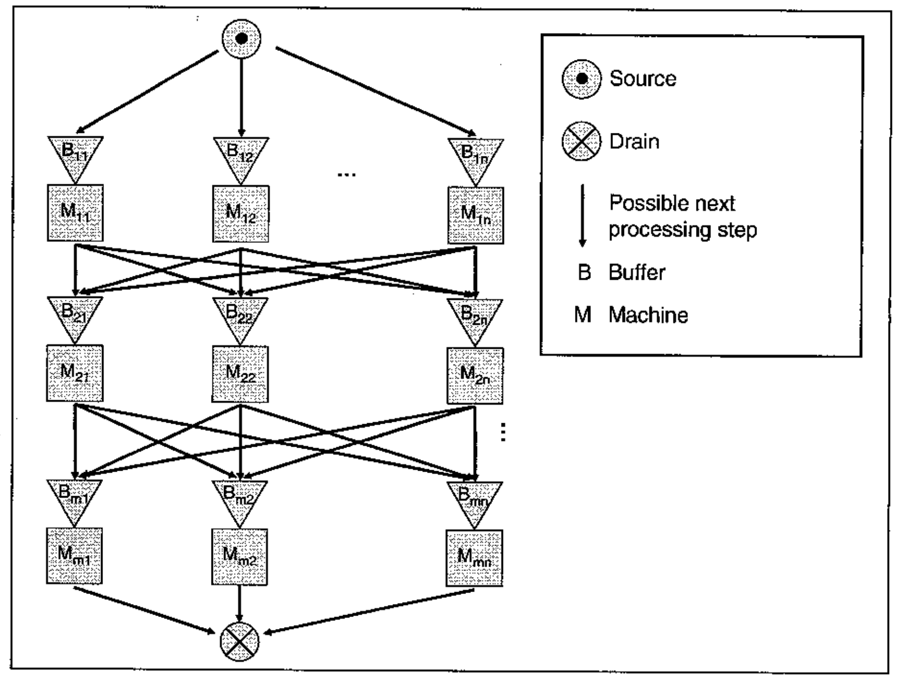

Fig. 9.1 Generic $m \times n$ shop floor scenario [14]

Table 9.1 Set-up times of the 3 × 3 machines model

Set-up times	Machine		
[min]	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

To handle the complexity, the simulation model is reduced to 3×3 machines producing 3 different product types A, B and C. The model is build with Vensim DSS computer simulation software. 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 of 1/3 period for the three product types. To model a usual workload of about 80% in real production systems, a mean arrival rate of 0.4 $1/h$ and an amplitude of the sine functions of 0.15 $1/h$ are chosen. It is assumed that the processing times for each product are the same: 120 min. Table 9.1 shows the set-up times for the three parallel machine types 1, 2 and 3 at all production stages m and the three product types respectively. To analyze the logistics performance of the global system, the aggregate buffer level for the three different product types of the first production step was chosen as the logistic performance indicator.

As there are different product types with different set-up times, the machines' service rule for the different product types is important. For the first simulation scenario it is first in – first out (FIFO).

To analyze the behavior of a flexible flow shop with more than one autonomous control strategy, the pheromone-based autonomous control strategy was chosen for scheduling. It uses data from past events in a way that every time a part leaves a machine after being processed, it leaves information about the duration of its processing and waiting time at the respective machine as an artificial pheromone. The following parts can use this information 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. To mimic the behavior of ants to search for shortest ways with the help of a random walk, the parts deviate from the decision to simply follow the strongest pheromone concentration with a certain probability (here 5%). 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 ($0 < E_{mnk} \ll 1$) for product type k at machine mn, β_{mnk} a (constant) gain 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:

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

This flexible flow shop scenario with autonomous scheduling was implemented with the help of the continuous System Dynamics Vensim DSS computer simulation software. The term continuous denotes the continuous material flow and evaporation process, which differs from the flow of discrete parts in e.g. a discrete event simulation model; the simulation time is discrete. In literature, continuous flow models of production systems are often called hybrid models (e.g. [6, 11]). That means the material flow is modeled as continuous flow which is controlled by discrete actions. This discrete control is typical for production systems. The implementation of the different autonomous service rules together with the simulation results are described in the following section.

9.4 Design of Autonomous Service Rules and Simulation Results

The simulation model is designed in a way that it allows the analysis of different service rules. First, and for comparison, the flexible flow shop with pheromone-based autonomous control is combined with FIFO service rule in Sect. 9.4.1. In Sect. 9.4.2 a pheromone-based service rule is presented, followed by a QLE service rule in Sect. 9.4.3. An evaluation of the results is given in Sect. 9.4.4.

9.4.1 Simulation Results with FIFO

Figure 9.2 shows the aggregate buffer levels of the first production step of the flexible flow shop with pheromone-based autonomous control for scheduling and FIFO as the service rule. The maximum inventory is 13.26 pieces and the mean inventory is 8.65 pieces with a standard deviation of 6.11 pieces.

9.4.2 Simulation Results with a Pheromone-Based Autonomous Service Rule

To improve the logistic performance the service rule should be altered. The approach to implement an autonomous service rule, i.e. let the machines select the parts and organize the set-ups, is promising, because set-ups are random in a FIFO scenario. The pheromone-based autonomous service rule works as follows: Set-up to the product type with the highest pheromone concentration and with some

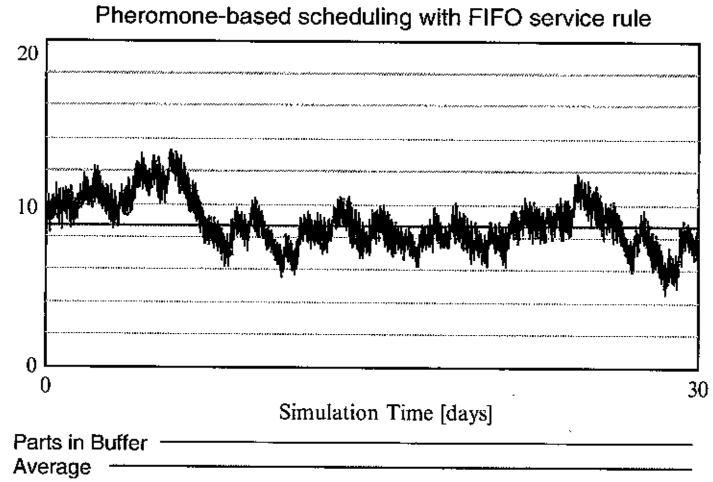

Fig. 9.2 Aggregate buffer levels of the first production step with FIFO

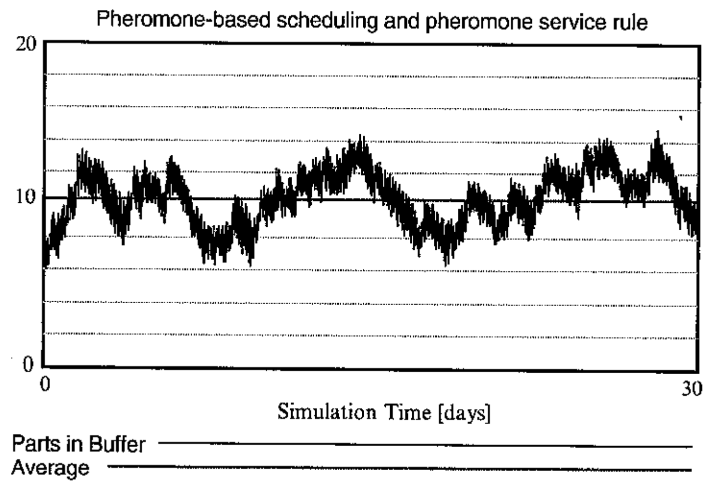

Fig. 9.3 Aggregate buffer levels of the first production step with pheromone-based service rule

probability (here 5%) set-up to a random product type. The pheromone update process is straightforward: Whenever a part has been processed it leaves an artificial pheromone according to its product type at the machine, which is constantly evaporating.

Figure 9.3 depicts the aggregate buffer levels of the first production step of the flexible flow shop with pheromone-based autonomous control for scheduling and the pheromone-based service rule.

The maximum inventory is 14.74 pieces and the mean inventory is 10.37 pieces with a standard deviation of 8.41 pieces. This performance is not satisfying; even the FIFO service rule shows a better performance within this scenario.

9.4.3 *Simulation Results with QLE as Autonomous Service Rule*

To further analyze the behavior of the flexible flow shop with multiple autonomous control strategies, the QLE is implemented as service rule. The QLE service rule is designed in a way that the machine calculates the total processing times, waiting times plus set-up times of each product type in its buffer. Then, it compares the values and chooses to set-up to the product type with the longest overall processing, waiting and set-up time to maximize periods without set-ups.

The aggregate buffer levels of the first production step of the flexible flow shop with pheromone-based autonomous control for scheduling and QLE service rule are shown in Fig. 9.4.

The maximum inventory is for pheromone-based scheduling and QLE service rule is 13.48 pieces and the mean inventory is 9.02 pieces with a standard deviation of 8.33 pieces. This performance is not good as well. Although better than the pheromone service rule, the QLE performance is slightly worse than FIFO.

9.4.4 *Evaluation of the Results*

At a first glance, it seems to be surprising that the performance of the autonomous service rules is bad and even below FIFO. When analyzing the drawbacks of the two new autonomous service rules, their lack of performance can easily be explained.

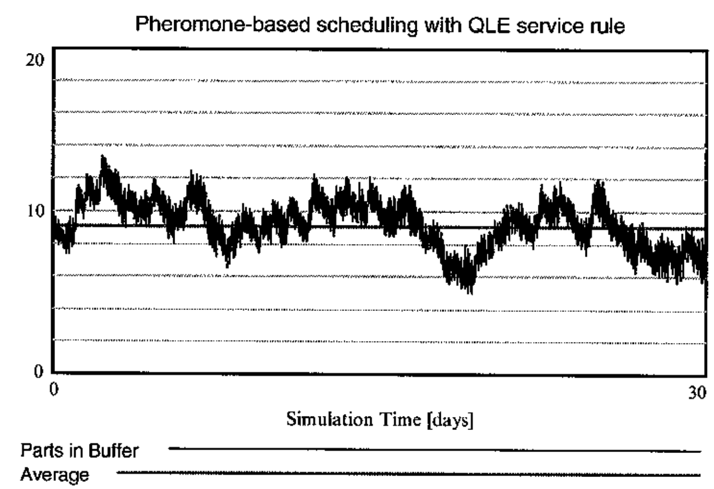

Fig. 9.4 Aggregate buffer levels of the first production step with QLE service rule

The pheromone-based service rule handles set-ups according to the predecessors experience and does not set-up to actual needs. For example, a set-up would be from product type A to product type B if there are no parts of product type A in the buffer and set-ups to product type B have been a good decision in the past. This decision is a very bad one if there are no parts of product type B in the buffer. A second drawback of the pheromone-based service rule is the deviation from the strongest pheromone concentration (analogous to the random walk of ants), which leads to completely senseless set-ups. These two drawbacks end up in the bad performance shown in Sect. 9.4.2. The pheromone-based autonomous control for scheduling does not take the pheromone-based service rule's drawbacks into account as there is no synchronization between the different autonomous control strategies.

The QLE service rule has two drawbacks as well: First, newly arriving parts lets the QLE re-calculate the overall time to clear the buffer from the respective product type. This leads to many set-ups according to the re-evaluated simulation. Another drawback of the QLE service rule is that the third-best alternatives, i.e. the ones with the longest set-up time, are processed in a subordinate way compared to the other service rules, because differing set-up times are not regarded at all in the scenario with pheromone-based service rule or FIFO. The pheromone-based autonomous control for scheduling does not take the QLE service rule's drawbacks into account either as there is again no synchronization between the different autonomous control strategies here.

Both logistic systems with a pheromone-based autonomous scheduling strategy and autonomous service rules show a very bad performance. A designer of autonomous control strategies is in a dilemma: Multiple autonomous control strategies within one logistic system do not perform well per se, neither do they synchronize themselves and without paying attention, the overall performance can be bad.

9.5 Solution to the Dilemma

Exemplarily, two different solutions to the dilemma described in Sect. 9.4.4 are presented in the following. First, an easy and non-autonomous service rule is implemented, which shows a very good performance. Another improvement can be achieved by introducing a correction term to the scheduling pheromone in order to synchronize the autonomous control strategies for scheduling and the autonomous control strategy for buffer clearance.

9.5.1 *A Simple But Good Service Rule*

A simple non-autonomous service rule is implemented. It minimizes set-ups in the following way: As long as there are parts of the type the machine is set-up to: do not make a set-up, go on processing. If a set-up is needed, switch to the type which is quantitatively best represented in the buffer. Figure 9.5 shows the aggregate buffer

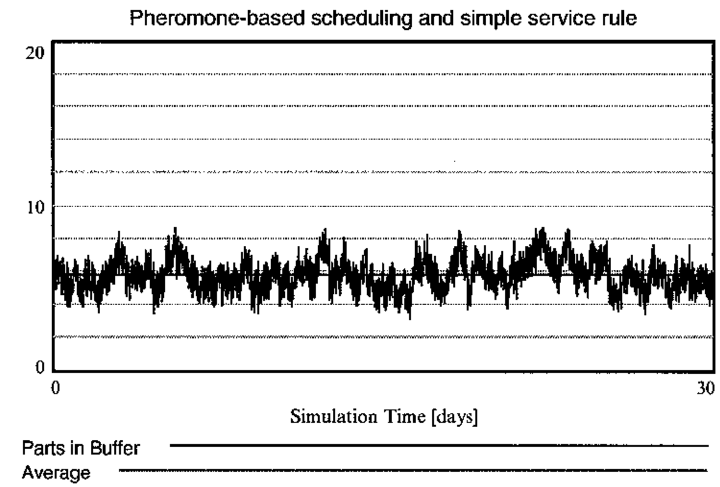

Fig. 9.5 Aggregate buffer levels of the first production step – pheromone-based scheduling with correction term and simple service rule

levels of the first production step of the flexible flow shop with pheromone-based autonomous control for scheduling and the simple service rule.

The maximum buffer level is reduced to 8.83 pieces. The mean buffer level is 5.77 pieces with a standard deviation of 3.88 pieces. The implementation of the simple service rule to let the machines select parts according to the mentioned scheme leads to an improved performance.

9.5.2 *Introducing a Pheromone Correction Term*

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 [15].

A correction term is introduced to the update process of the pheromone concentration. This correction term includes information about the product type a machine is set-up 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 ($1 > EC \gg E$) 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 $CT_{mnk}(t)$:

$$P\_cor_{mnk}(t) = P\_part_{mnk}(t) + CT_{mnk}(t)$$

with

$$P\_part_{mnk}(t) = P\_part_{mnk}(t) - P\_part_{mnk}(t-1)E_{mnk} + \begin{cases} \beta_{mnk} TPT_{mnk}(t), & \textit{if 'machine has completed its job'} = \textit{true} \\ 0, & \textit{else} \end{cases}$$

and

$$CT_{mnk}(t) = CT_{mnk}(t) - CT_{mnk}(t-1)EC_{mnk} + \begin{cases} \delta_{mnk}, & \textit{if set-up\_status}_{mnk}(t) = k \\ 0, & \textit{else} \end{cases}$$

The (higher) evaporation constant for the correction term EC_{mnk} is adjusted to the execution time (processing time plus set-up time) of the next part on a particular machine in order to improve the overall performance of the logistic system. Figure 9.6 shows the aggregate buffer levels of the first production step with

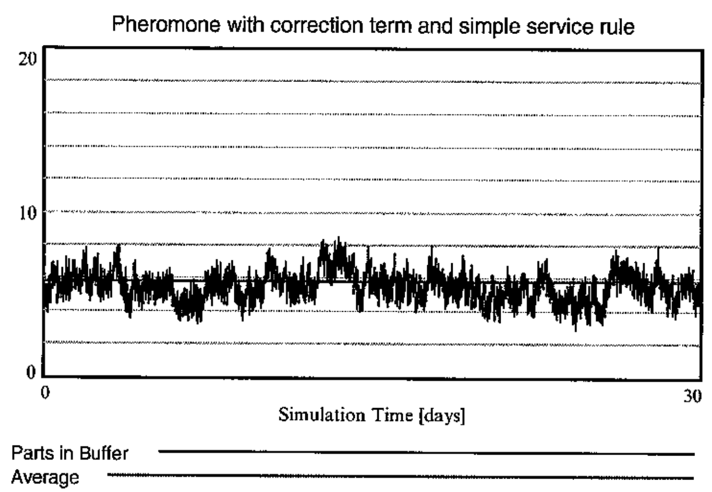

Fig. 9.6 Aggregate buffer levels of the first production step with pheromone-based scheduling with correction term and simple service rule

Table 9.2 Performance measures of the different service rules and the altered pheromone-based scheduling strategy

	FIFO (4.1)	Pheromone based service rule (4.2)	QLE service rule (4.3)	Simple non-autonomous service rule (5.1)	Pheromone with correction term (5.2)
Mean	8.65	10.37	9.02	5.77	8.55
Max	13.26	14.74	13.48	8.83	5.51
STD	6.11	8.41	8.33	3.88	3.67

pheromone-based scheduling with correction term and the simple new service rule for buffer clearance 5.1).

With the help of the pheromone correction term the maximum buffer level is reduced to 8.55 pieces. The mean buffer level goes down to 5.51 pieces with a standard deviation of 3.67 pieces. The implementation of the pheromone correction term pays as the comparison of FIFO (cf. 4.1), pheromone-based service rule (cf. 4.2), QLE service rule (cf. 4.3) and simple service rule (cf. 5.1) in Table 9.2 summarizes.

One has to keep in mind that introducing a correction term to the scheduling pheromone means abandoning the use of strictly local data because of the interaction between the machines (their set-up status is local information) and the pheromone-based autonomous control strategy for scheduling.

9.6 Summary and Outlook

A generic matrix model of a flexible flow shop with set-ups and a pheromone-based autonomous control strategy was presented to analyze the performance and behavior of multiple autonomous control methods within one logistic system. Two autonomous service rules for buffer clearance, a pheromone-based service rule and the QLE service rule were introduced and implemented into a System Dynamics computer simulation model. The simulation results were compared to the FIFO service rule and it was shown that the overall performance of the autonomous service rules was bad, even worse than FIFO, in this scenario.

One big result of this contribution is that the application of autonomous control has its limitations: Multiple autonomous control strategies within one logistic system do not perform well per se, neither do they synchronize themselves. Designers of autonomous control strategies should beware: Autonomous control should not be implemented for the sake of autonomous control itself. Designing autonomous control methods according to current requirements as well as synchronization is highly needed (and possible).

Two solutions to the dilemma were introduced: First, a simple service rule for buffer clearance showed a better performance. Second, the interaction between buffer clearance and scheduling was improved by introducing a pheromone correction term to the autonomous control strategy for scheduling. This course of action showed on the one hand an improved performance, on the other hand leads this