Dynamics of Autonomously-Acting Parts and Work Systems in Production and Assembly

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Abstract
Autonomous production is characterized by local decision making of intelligent logistic objects such as work systems that autonomously adjust production rates and parts that autonomously decide which products they "want" to become. It is important to understand dynamic interactions of these objects and their resulting performance. Results of simulation studies and control-theoretic modeling of decision-making by autonomous logistics objects in the example reported in this paper show that such dynamic interactions can be well behaved and predictable. Tools of control theory are shown to be useful when decision-making logic is modeled in a way that makes control-theoretic analyses tractable.

Keywords
Autonomous, Production, Dynamics

1 INTRODUCTION

It is becoming increasingly difficult to ignore the fact that the complexity and the dynamics of modern supply chains have a major impact on the performance of manufacturing enterprises. It has been shown that dynamic complexity drivers significantly affect the performance of manufacturing plants [1] and that supply chain complexity, including technology and information processing, significantly affects delivery performance [2]. Questions have been raised regarding the ability of present production planning and control methods to handle this challenge with their centralized control approach.

In recent years, researchers have proposed a paradigm shift from centralized to de-centralized control approaches as a way to cope with this complexity [3]. A newly established concept of de-centralized control, called autonomous control and characterized by decentralized decision-making in heterarchical systems [3], aspires to provide logistic objects with decision capabilities. The most significant difference between heterarchical and hierarchical systems is that objects can operate independently from each other and have equal rights to access resources [4]. With the highest level of autonomous control master-slave relationships are eliminated, global information sharing is avoided, and intelligent objects make decisions based on local information and a minimal amount of information obtained from other objects [5].

The behavior of these heterarchical systems depends strongly on the local decision making logic that is implemented [6]. The underlying hypothesis is as follows: By enabling logistic objects to make decisions on their own, the level of autonomous control rises and the overall achievement of logistic objectives, e.g. short delivery times, high due date reliability, low capital tie-up costs, desired capacity utilization, can be increased. Figure 1 illustrates the assumed relationship between degree of autonomous control within a production system and achievement of logistic targets. Today's production systems operate on a relatively low level of autonomous control. By increasing it, the remaining logistic potential can be developed and a higher logistic target achievement can be reached. Unfortunately, without global information, de-centralized decision making can converge to local rather than global optima. Therefore, it is important to understand the dynamic behavior of autonomous production in order to avoid undesired characteristics that diminish performance.

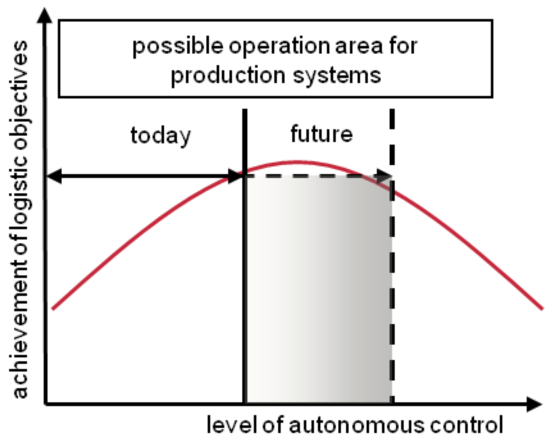


Figure 1: Domain of operation for production systems (based on [7]).

Various concepts have been investigated for autonomous control in production including concepts based on Internet routing protocols [8] and biological examples such as ants [9] and bees [10]. Levels of autonomy in production logistics have been characterized, including requirements for decision alternatives within production processes [11]. Control-theoretic concepts have been developed for local regulation of work-in-process (WIP) [12] and lead-time [13] by autonomous work systems.

The purpose of the work reported in this paper was to study and characterize the dynamic interaction of autonomous parts and autonomous work systems. This is of interest because different kinds of logistic objects can pursue individual and possibly conflicting objectives. Parts, for example, can try to navigate through production in the fastest possible way by choosing work systems with short waiting queues [10], while work systems can try to maintain ideal WIP [12] because WIP determines capital employed and influences both capacity utilization and throughput times [14]. During production, autonomous parts and work systems make a multitude of decisions. Hence, as individual logistic objects pursue object-specific goals, their resulting interacting dynamic behavior is of essential importance.

The paper begins with an introduction of the concept of autonomous part manufacturing using autonomous work systems. Simulation results are then used to illustrate dynamic behavior and show proof of concept. After that, a control-theoretic model is presented that permits quantitative characterization of the interacting dynamic behaviors of the logistic objects and desirability of the resulting performance. Finally, the results of the simulation studies and control theoretic analyses are compared, and conclusions are drawn regarding the efficacy of pairing autonomous parts with autonomous work systems in production, as well as the utility of control-theoretic analysis in this domain.

2 AUTONOMOUS MANUFACTURING

Regardless of the decision-making logic used, the number of possible decision alternatives is crucial for the success of autonomously controlled processes. The more decisions with various decision alternatives that exist within a logistic system, the higher the logistic potential that can be realized with autonomous control methods [11]. In the following subsections, the concepts of autonomous parts and autonomous work systems are defined and the nature of their decision alternatives and interactions is discussed.

2.1 Autonomous parts

Traditionally there is a fixed link between orders and parts in the series manufacturing of products with many variants; i.e., the production plan of parts is predetermined and allows for few or no flexibility during the production process. Hence, in the case of customer order changes or production failures, only little room for logistic maneuvers exists. By removing the fixed link between customer orders and parts produced, inherent but so far unused flexibility potentials can be developed.

Figure 2 shows the decision space for an autonomous part. The autonomous part can decide the next production operation and choose among the available production resources the one that should perform the operation. In making this decision, it should also take into account the different final product variants it can become and the current demand situation; i.e., the customer orders for this product variant.

In order to select a decision alternative from the available decision space, a general decision function (Equation 1) can be formulated. The function needs to yield the selected production operation *ps* and the selected work system *ws* to perform the operation. Furthermore because the linkage between customer order and part is loose, the decision function needs to return the set of still possible product variants *pv* as well as the set of customer orders *co* that still can be satisfied at rest:

$$[ps, ws, pv, co] = \mathrm{f}_{\mathrm{dm}}(c_1, c_2, \ldots, c_n) \tag{1}$$

The selection of the decision alternative is based on the applied evaluation criteria (c_i, i=1,2,…,n). The autonomous part therefore not only decides about the actual process step and the work system on the shop floor, but also about the product variant and the respective customer demand it serves. Consequently, the decision logic can take into consideration both the actual situation on the shop floor (machine breakdowns, dynamic bottlenecks, missing tools or raw material, etc.) and the actual demand situation (late order cancellation, due date shifting, quantity variation, variant modification, etc.).

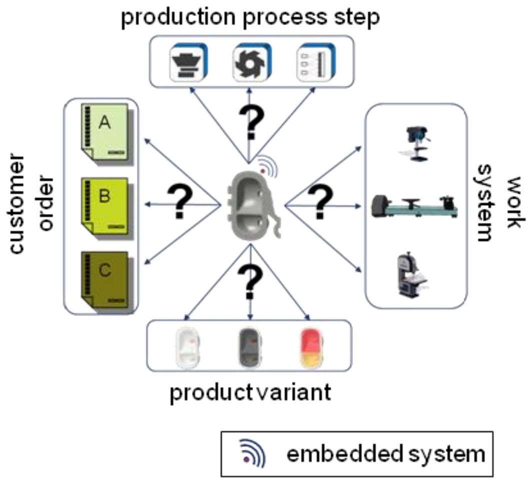


Figure 2: Decision space of an autonomous part.

2.2 Autonomous work systems

An autonomous work system may need to perform two types of decision making: sequencing and capacity adjustment. Sequencing is the task of selecting the next part to process from the waiting queue in front of the work system. With the First-In-First-Out (FIFO) sequencing rule, parts are processed in the same sequence as they arrive at the work system. Other sequencing rules may involve examining the processing times and due dates of parts in the queue and choosing the optimal part according to a given merit function or, for example, choosing the part with the shortest or longest processing time or the earliest due date [4]. However, in lean manufacturing, lower WIP levels are desired and the influence of sequencing rules at these low WIP levels is low [15], making the simple FIFO rule a good choice.

Capacity adjustment decisions involve extending or reducing the time of operation, increasing or decreasing the number of machines or human operators in the work system, etc. This can be necessary in order to react to machine breakdowns or demand fluctuations [15]. The WIP level is a crucial factor in a work system because it influences both utilization and lead times. While a high-level plan may be available, estimating the capacity required to satisfy part production requirements, work systems must be agile in order to react to demand variations that cannot be fully anticipated due to decisions made by autonomous parts.

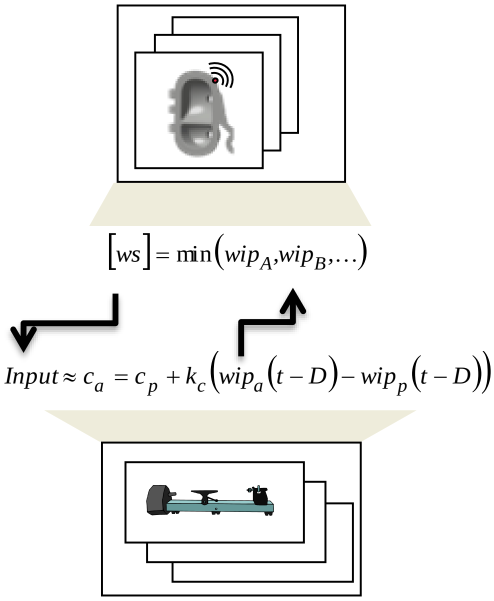
2.3 Interaction of intelligent objects

The focus of the work described in this paper was on the interaction of autonomous logistic objects; specifically, autonomous parts and work systems. The interaction between these objects results from their mutual dependency on information for decision making.

Figure 3 illustrates this dependency in the case where parts chose the next work system based on the length of the waiting queue (WIP) at the work systems. Work systems, on the other hand, make capacity adjustments with respect to a planned capacity $c_p(t)$ at time t based on the difference between actual WIP $wip(t)$ and planned (desired) WIP $wip_p(t)$ as described by the following rule:

$$c_a(t) = c_p(t) + k_c(wip(t-D) - wip_p(t-D)) \tag{2}$$

where k_c is a parameter that determines the magnitude of capacity adjustments with respect to deviation of WIP from the desired WIP level, and hence the time required to eliminate such deviations. D is a delay in adjusting capacity that may be necessary due to logistic realities such as work rules. Work system capacity can be adjusted every T days, and delay D is an integer multiple d of period T ($D = dT$.). The input of a work system has to be in balance with its actual capacity over time; otherwise, the work system becomes either a bottleneck or idle. Decisions made by parts, based on work system WIP, obviously affect work system WIP and the capacity adjustments made by the work systems.



ws:	selected work system
wip_A:	wip at work system A
wip_B:	wip at work system B
c_a:	actual capacity
c_p:	planned capacity
k_c:	wip regulation parameter
wip_a:	actual wip
wip_p:	planned wip
D:	delay in capacity adjustment
t:	time

Figure 3: Interacting autonomous parts and work systems.

3 HYBRID SIMULATION MODEL

A simulation model was developed for production of parts that autonomously decided, at each production step, at which of several work systems they were to be processed. Work systems processed parts on a FIFO basis and each day, each work system autonomously adjusted its full capacity with the goal of maintaining local WIP at a planned level. Capacity adjustments were determined using Equation 2 with a delay of one day in applying calculated capacity adjustments. Both capacity disturbances such as equipment failures and work disturbances such as rush orders were possible. The simulation was implemented in object-oriented Matlab in a hybrid manner [16], with agent-based simulation of part and work system decision making and time-scaled simulation of part processing by work systems.

Results of the simulation of a simple decision-making scenario are shown in Figure 4(a) where only one type of part was processed at two work systems: Work Systems A and B. Individual machines and their human operators were not modeled, and each work system therefore was considered to be a single logistic entity that had variable daily production capacity (hours of work per day). Each part had only one processing step and, upon being released, routed itself to the work system with less WIP. Each part autonomously made this decision based on WIP information obtained from the work systems. Ten new parts were released each morning for production, and each required one hour of processing by either work system. The capacity adjustment parameters were k_c=0.25 day^{-1}, T=1 day, d=1 (dT=1 day), c_p=5 hours/day and wip_p=5 hours.

On day 10, a capacity disturbance was introduced that reduced the capacity of Work System A by 2.5 hours/day. Such a disturbance could be caused, for example, by the absence of a human operator. It can be observed in Figure 4(a) that both work systems adjusted their capacities upward. This could be achieved, for example, by employees working overtime. These capacity increases were generated by increasing WIP in Equation 2; WIP nearly doubles in this example due to the capacity disturbance. However, the WIP in the two work systems remains nearly equal, even during the transient phase of the response, because decision making by parts was based on lowest WIP. When the work systems reach their new steady capacities, after about 9 to 10 days, the sum of their capacities equaled the rate of work input, preventing further increases in WIP. As expected, more parts route themselves each day to Work System B than Work System A. The dynamic interactions between the autonomous parts and autonomous work systems in this example were well behaved and reasonable in reacting to the capacity disturbance.

4 CONTROL-THEORETIC MODEL

A control-theoretic model was developed that approximately represented the dynamics of part decision-making logic and WIP regulation for the example described above. As the first step in control-theoretic analysis, the fraction of the input flow rate $i(t)$ that went to Work System A and Work System B, $i_A(t)$ and $i_B(t)$ respectively, as a result part decision making was approximated using

$$f_A(t) = \frac{p_{1B}}{p_{1A} + p_{1B}} + \frac{wip_B(t) - wip_A(t)}{p_{1A} + p_{1B}} \tag{3}$$

$$f_B(t) = 1 - f_A(t) \tag{4}$$

$$i_A(t) = f_A(t)i(t) \tag{5}$$

$$i_B(t) = f_B(t)i(t) \tag{6}$$

where p_A and p_B are the processing times of the part type on Work Systems A and B, respectively, and $wip_A(t)$ and $wip_B(t)$ are the WIP in Work Systems A and B, respectively, at some time t. For example, if $WIP_A(t)$-$WIP_B(t)$=0 and P_A=P_B in Equation 3, then $f_A(t)$= $f_B(t)$=0.5 and $i_A(t)$=$i_B(t)$=0.5$i(t)$. On the other hand, if $WIP_A(t)$-$WIP_B(t)$=P_A=P_B, then $f_A(t)$=0, $f_B(t)$=1, $i_A(t)$=0 and $i_B(t)$= $i(t)$.

Equations 5 and 6 can be linearized at a nominal input-rate and WIP-difference operating point, yielding

$$i_A(t) \approx a\left(wip_B(t) - wip_A(t)\right) + b_A i(t) - d \tag{7}$$

$$i_B(t) \approx a\left(wip_A(t) - wip_B(t)\right) + b_B i(t) + d \tag{8}$$

where $\bar{i}$ is the nominal input rate,

$\overline{wip_B - wip_A}$ is the nominal WIP difference, and

$$a = \frac{\bar{i}}{p_A + p_B} \tag{9}$$

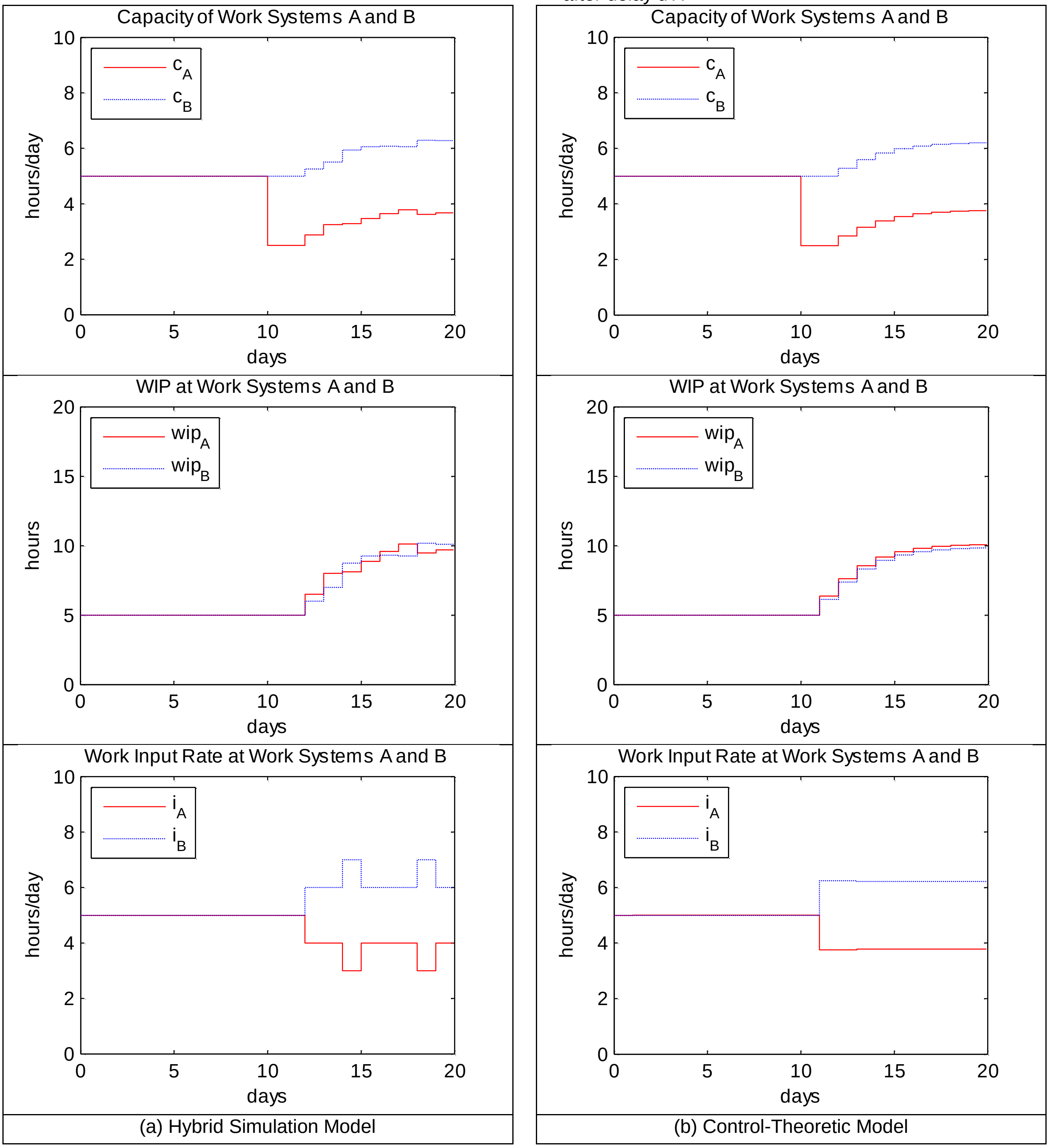
$$b_A = \frac{p_B + \overline{wip_B - wip_A}}{p_A + p_{1B}} \tag{10}$$

$$b_B = \frac{p_A - \overline{wip_B - wip_A}}{p_A + p_B} \tag{11}$$

$$d = \frac{\bar{i}}{p_A + p_B}\left(\overline{wip_B - wip_A}\right) \tag{12}$$

The control-theoretic model is shown in Figure 5, where c_A and c_B are the actual capacities of Work Systems A and B, respectively, w_{dA} and w_{dB} are work disturbances, and c_{dA} and c_{dB} are capacity disturbances. The model was implemented in Matlab in discrete state-space form, allowing response to disturbances and fundamental dynamic properties to be calculated.

It was assumed that WIP is measured at instants in time separated by T and compared to wip_{pA} and wip_{pB}, planned (desired) WIP in Work System A and B, respectively. Then, capacity adjustments Δc_A and Δc_B with respect to planned capacities c_{pA} and c_{pB} were calculated according to Equation 2, producing the full capacity for each work system that was implemented after delay dT.



(a) Hybrid Simulation Model

(b) Control-Theoretic Model

Figure 4: Daily capacity, WIP and work system input rate.

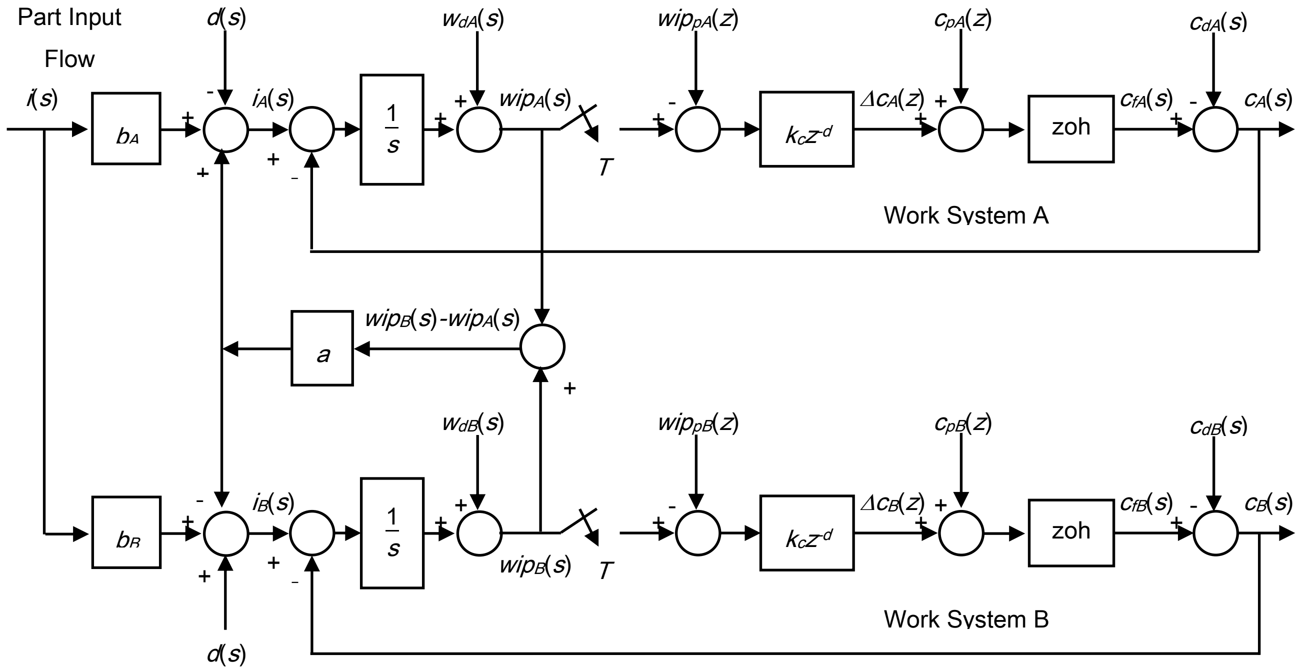


Figure 5: Control-theoretic model.

With capacity adjustment period T=1 day, delay d=1, control parameter k_c=0.25, 10 hours per day nominal input rate, and zero nominal WIP difference, the system was theoretically well-behaved and has had dominating characteristic time of 1.44 days. Figure 4(b) shows the response of the linearized control-theoretic model to a constant capacity disturbance of 2.5 hours/day that begins on day 10. As in Figure 4(a), the decisions made by parts tend to keep the difference in WIP between the two work systems nearly zero. Comparing Figure 4(b) to Figure 4(a), it can be seen that, while the discreteness associated with each part is not represented in the control-theoretic model, capacity, WIP and input flow in Figure 4(b) follow similar trajectories and reach final values that are identical to the means reached in the hybrid simulation model shown in Figure 4(a).

The characteristic times calculated using the model in Figure 5 are listed in Table 1 for a=0.2 days^{-1} (10 parts/day nominal input rate, p_A=p_B=1 hour in Equation 9), as well as a=0.4 days^{-1} and a=0.1 days^{-1}. These results indicate that the dominating characteristic time of 1.44 days, which is associated with WIP regulation, does not change with the operating point, and response to disturbances is complete after 9 to 10 days based on these characteristic times, daily adjustment of capacity, and delay of one day in applying capacity adjustments.

Table 1: Characteristic times predicted by the control-theoretic model (a is defined in Equation 9)

a=0.1 days^{-1}	a=0.2 days^{-1}	a=0.4 days^{-1}
1.44	1.44	1.44
1.44	1.44	1.44
0.66	0.54	0.46
0.66	0.54	0.46

5 CONCLUSION

The dynamic interactions between autonomous logistic objects, specifically autonomous parts and autonomous work systems, were studied using both hybrid simulation and control-theoretic analysis. A relatively simple scenario was used to illustrate the dynamics of these interactions. In the example, individual parts chose the work system with lowest WIP for processing, and individual work systems adjusted their capacity to maintain WIP at a planned level. Decisions made by parts therefore affected work system WIP, which was also affected by capacity adjustments made by work systems. Both hybrid simulation and control-theoretic analysis showed that the decision rules used resulted in production results that were dynamically well behaved and reasonable, including effective reactions to disturbances. These results provide evidence that paring of autonomous parts and autonomous work systems can result in effective autonomous production. Additional research is needed to more fully understand and characterize the dynamic behavior of production systems in which the logistics of product variants and customer orders are handled by autonomous parts that incorporate more complex decision rules and interact with autonomous machines and work systems.

To make control-theoretic analysis tractable, the decision-making logic used by the autonomous parts was approximated by equations modeling fractional work flows to work systems. These equations then were linearized given the expected work input rate and desired WIP in the work systems. This allowed fundamental dynamic properties of the interactions between logistic objects to be predicted and assessed. Responses predicted by hybrid simulation and control-theoretic analyses were similar; differences were primarily due to neglecting the discrete nature of individual parts in the control-theoretic model. The dominating characteristic times of response calculated using control-theoretic analysis were found to be favorable, constant for a range of operating conditions, and in agreement with simulation results. The control-theoretic models provided significant insight into fundamental dynamic behavior of interacting autonomous logistic objects.

6 ACKNOWLEDGMENTS

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