Look-ahead Strategies for Controlling Batch Operations in Industry – Overview, Comparison and Exploration

D.J. van der Zee[1]

[1]Department of Production Systems Design, Faculty of Management and Organization, University of Groningen, P.O. Box 800, 9700 AV Groningen, The Netherlands

SOM-theme A Primary processes within firms

Abstract

Batching jobs in a manufacturing system is a very common policy in most industries. Main reasons for batching are avoidance of set ups and/or facilitation of material handling. Good examples of batch wise production systems are ovens found in aircraft industry and in semi-conductor manufacturing. Starting from the early nineties much research efforts have been put in constructing strategies for the dynamic control of these systems in order to reduce cycle times. Typically, these so-called “look-ahead strategies” base their scheduling decision on the information on a few near future product arrivals. In this paper we give a literature overview of the strategies developed so far, evaluate their performance and explore their relevance for practical situations by means of a simulation study.

1 INTRODUCTION

“To start the machine now or to wait for a next customer to arrive”, that is the question which stresses the essence of the control task for many batch processing systems. The trade-off includes the balancing of logistic costs (e.g. stock keeping, machine utilization) on the one hand and customer service (e.g. lead-times, lead-time uncertainty) on the other hand. As such it is a very common problem found in many industries. In this article we survey strategies which assist the planner in solving the problem efficiently. The type of systems we study here are ovens found in e.g. the aircraft industry and semiconductor manufacturing, cf. Glassey et. al. (1991,1993), Hodes et. al. (1992), Uzsoy et. al. (1992,1994). Both industries are highly competitive. Therefore, lead time reductions and improvements of the service level are of vital importance.

Starting in the early nineties (cf. Glassey, 1991) much research efforts have been put in constructing “look-ahead strategies which solve the problem efficiently. Typically, these types of strategies base their decision on the knowledge of some near future arrivals. In this paper we relate these strategies to alternative types of strategies, such as threshold strategies and (deterministic) scheduling rules. Given this classification we give a literature overview and compare rules for their performance for several criteria by means of a simulation study. In order to resemble practical situations the study includes robustness tests for cases in which data on future product arrivals are forecasted or even unknown. Finally, we will explore the practical benefits of look-ahead strategies by. The basic question which will be addressed is: how do system parameters influence relative performance of look-ahead strategies?

The paper is organized as follows: in Section 2 main characteristics are described for the studied system. As a starting point we use case examples from aircraft and semiconductor industry. In Section 3 we address the control problem by giving an overview of developed look-ahead strategies. The potential of the look-ahead strategies is demonstrated in Section 4. By an extensive simulation study strategies are compared for their performance. Section 5 addresses the use of look-ahead strategies for practical situations. In this section we evaluate system performance for a wide range of system configurations as far as product and machine characteristics are concerned. Finally, in Section 6, conclusions are drawn and suggestions are made for future research.

2 SYSTEM DESCRIPTION

A typical *batch process* in aircraft industry concerns the hardening of synthetic parts (cf. Hodes et. al. 1992). This process is characterized by specific settings for temperature, pressures and service times, which relate to different products. Typically, different products cannot be batched together. *Batch sizes* are limited by the physical size of the oven and by a process constraint, which determines a maximum fill rate for the oven. *Service times* are considered to be constant (including sequence independent set up times), depending on product and/or oven characteristics. Preemption of jobs is not allowed because this would make products worthless for any further use. This is due to strict quality constraints.

Batch processing systems that are similar to the system described above can be found in many industries. For example the ovens used for diffusion/oxidation in the semiconductor manufacturing (see e.g. Fowler et. al. (1992), Uzsoy et. al. 1992). Further some other systems can be found which have more or less similar characteristics, like ferries, elevators and restaurants, cf. Bagchi et. al. (1972), Deb et. al. (1973), Hopp et. al. (1996).

3 LOOK-AHEAD STRATEGIES – AN OVERVIEW

The described systems are known in literature as bulk queuing systems. Bulk queuing systems are characterized by the fact that customers arrive in groups and/or are served in groups by one or multiple parallel machines (compare Figure 1). In Van der Zee et. al. (1997a) it is shown how control strategies for bulk queuing systems may be classified according to the amount of information which is known on future arrivals of customers. Three typical situations can be distinguished:

1. No information available
2. Full knowledge of future arrivals
3. A limited number of near future arrivals are known or predicted

The first situation corresponds to settings in which only local information on queue length is available. The most important example of a strategy addressing suchlike situations is the Minimum Batch Size rule (MBS), which was introduced by Neuts (1967). According to this strategy a batch starts service as soon as at least a certain fixed number of customers is present. Using a dynamic programming approach, Deb and Serfozo (1973) showed how this critical load should be chosen in order to minimize the expected discounted cost over an infinite horizon. If the cost of serving is set to zero and the cost of waiting is linear, minimizing the expected averaged cost is equivalent to minimizing the average flow time.

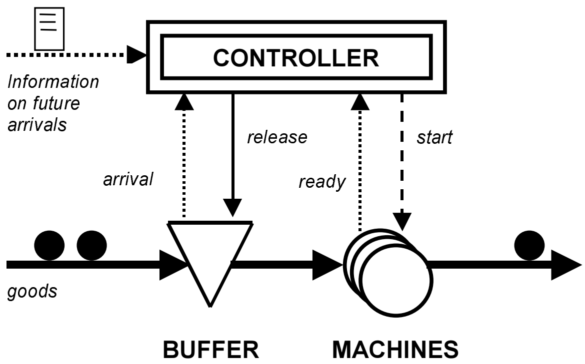

Figure 1: Control of a batch shop

While the above types of strategies assume zero information on future arrivals, full knowledge of such arrivals is supposed to be available when it comes to deterministic machine scheduling. An overview of this type of strategies is given by Uzsoy et. al. (1994), who discusses planning and scheduling models applicable to the semiconductor industry. The relevance of this type of models is quite limited because, in practice often only little information on future arrivals is available.

In this article we address the third situation. Therefore we focus on the so-called *look-ahead strategies*. Glassey and Weng (1991) were among the first to introduce this type of strategies for (semi-conductor) batch processing systems, which are characterized by the fact that they assume a few near future arrivals to be known and/or predicted. They discuss the practical usability of a dynamic programming approach to find a sequence of loading times of given lots, in such a way that total delay is minimized. They argue that this approach fails for reasons of computational feasibility, and availability and quality of data on future arrivals. Therefore they present a Dynamic Batching Heuristic (DBH). This heuristic decides when to start a production cycle thereby aiming for a minimal average flow time. The planning horizon in DBH is just one service time. DBH proves to perform better than MBS, based upon the knowledge of just a few arrivals. Starting from the single product single machine shop discussed by Glassey and Weng other authors proposed new look-ahead strategies in order to deal with several extensions (see Table 1).

The first extension of the DBH rule concerned the multiple products case, which was considered by Fowler et. al. (1992). Here products may differ as far as service time or maximum batch size is concerned. Their Next Arrival Control Heuristic (NACH) proves to be a robust heuristic in case forecasted data on future arrivals are used, i.e., estimated arrival moments for new lots. Weng et. al. (1993) show how performance can be improved for the multiple product single machine case by their Minimum Cost Rate heuristic (MCR), which shows an analogy with the Silver and Meal heuristic (1973). However, a disadvantage of MCR is the relatively large amount of data needed to realize the improvement in system performance. Also robustness of the heuristic is weaker than for NACH. For that reason Robinson et. al. (1995) propose a slightly altered and more robust version of the MCR heuristic, named Rolling Horizon Cost Rate heuristic (RHCR). Above that, they also show how this heuristic can be extended to the case of a batch – serial system. Here the production system consists of a batch machine followed by a serial machine, which processes piece-wise. In two articles Van der Zee et. al. (1996,1997a) introduce the Dynamic Job Assignment Heuristic (DJAH). It covers the multiple machine case and allows for compound arrivals. The criterion for optimization for DJAH is the minimization of logistic costs

Table 1: Overview of Developed Look-Ahead Strategies

Strategy	Number of machines (1,M)	Machine Char. (I,NI)	Number of products(1,N)	Product Char. (I,NI)	Batch arrivals (1,B)	Forecast data (Yes,No)	Criterion (F,C)
MBS	M	I	1	I	1	-	F,C
DBH	M*	*	1	*	1	No	F
NACH	1	I	N	NI	1	Yes	F
MCR	1	I	N	NI	1	No	F,C**
RHCR	1	I	N	NI	1	Yes	F,C**
DJAH	M	I	N	NI	B	Yes	F,C
DSH	M	I,NI	N	NI	B	Yes	F,C

Legend
MBS = Minimum Batch Size rule (Neuts, 1967)
DBH = Dynamic Batching Heuristic (Glassey et. al., 1991, 1993)
NACH= Next Arrival Control Heuristic (Fowler et. al., 1992)
MCR = Minimum Cost Rate heuristic (Weng et. al., 1993)
RHCR = Rolling Horizon Cost Rate heuristic (Robinson et. al., 1995)
DJAH = Dynamic Job Assignment Heuristic (Van der Zee et. al., 1996, 1997a)
DSH = Dynamic Scheduling Heuristic (Van der Zee et. al., 1999)

I = Identical machine(product) characteristics only (service time, allowed batch size)
NI = Non-identical machine(product) characteristics allowed (service time, allowed batch size)
F = Average flow time
C = Logistic costs
* = No explicit formulation available in literature
** = See Van der Zee et. al. (1997a)

per part (customer) on the long term. Logistic costs associated with a job consist of linear waiting costs and a fixed amount of set up costs (e.g. energy costs). The definition of this cost function also covers an important special case: if set up costs are zero, minimization of logistic costs comes down to minimization of average flow time (cf. Fowler et. al. (1992)). Although the DJAH heuristic proved its strength as a control strategy for multiple identical machines, it is less suited for those situations where alternative machine types are available. Here, the choice for different types of machines may be based on the required processing conditions (e.g. temperature, pressure), product characteristics (e.g. volume, dimensions) or operating costs (e.g. set up costs) or it is simply a matter of a historical growth pattern. To deal with these situations the Dynamic Scheduling Heuristic (DSH) was developed which strongly focuses on finding a good fit of machine and product characteristics (Van der Zee 1999).

4 COMPARISON OF STRATEGIES

In order to compare the performance of the developed heuristics they were extensively tested by a series of simulation experiments. Their response for various system configurations, which reflect different settings for product specifications and number of machines, was analyzed. The simulations which were carried out concern single/multi-product and single/multi-machine configurations. To enable judgement on the relative performance of the heuristics, for each of these cases different settings were studied. To allow for comparison of simulations, our settings have been derived from cases already mentioned in the literature, cf. Glassey et. al. (1991), Fowler et. al. (1992).

The package which was used to carry out the simulation experiments is ExSpect (Bakkenist 1994). ExSpect is a Petri Nets-based analysis tool. It allows for structural analysis as well as dynamic analysis by simulation. To facilitate the modeling process a logistics reference model was adopted (Van der Zee et. al., 1997b). A simulation model built according to this reference model can easily be adapted to incorporate new control rules or even new control structures. Moreover, the principles of object oriented design (see e.g. Booch, 1994) underlying both ExSpect and the reference model, guarantee reusability of model components in order to support further research.

4.1 Experimental Factors

In Table 2 an overview is given of experimental factors and their range. Four series of experiments are mentioned (I-IV). Experiments differ as far as the number of products (N) and the number of machines (M) is involved.

Two different criteria were applied to analyze the performance of the control strategies: the average flow time criterion and the minimal cost criterion. While the first criterion was applied to all control strategies, the latter criterion was only applied to MBS, MCR and DJAH, because NACH and DBH do not consider logistical costs nor can they easily be extended to do so (see Section 2). For all simulations operating costs were chosen uniformly: waiting costs equal 1 per unit of time, while set up costs constitute a fixed amount of 60. Note that we did not include RHCR in the simulations. The reason for this is that research by Robinson et. al. (1995) already showed that if there is no error in the prediction of future arrivals, simulation results for MCR and RHCR are almost identical. On the other hand they showed that if forecasting errors are introduced, RHCR yields no better results than NACH.

For each scenario one basic setting (default setting) has been defined which reflects a particular setting for product and machine characteristics. These settings are marked boldly in Table 2. Alternative system configurations were chosen by changing the value for exactly one of these decision variables. For example, to estimate the effect of a longer processing time on the system performance in the single product single machine case, the processing time was set to 50 time units instead of 25. In the same way the *robustness* of the heuristics, reflected by its response to forecasting errors or incomplete data on future arrivals, was evaluated. Forecasting errors are assumed to be normally distributed with mean equal to zero and a standard deviation which equals half the standard deviation of the interarrival times ($1/\lambda$). In the simulation model forecasting errors are associated with the data the decision maker receives on future arrival moments. Note that the possibility of forecasting errors requires a more refined updating of the information set on future arrivals (AR). At each decision moment corresponding with a product arrival the forecasted arrival moment for this product is removed from AR. Further, for decision making arrivals that are forecasted at t, but in 'reality' occur at $\tilde{t}$ later than t, are ignored once the decision moment t_0 passes t.

Also performance for heuristics in situations in which the decision-maker lacks on average 50% of the data on future arrivals is tested. These situations are modeled by associating a chance of 0.5 with each arriving product that it is not reported to the decision-maker before its actual arrival. As a consequence the heuristics have to base their decision on the knowledge of later arrivals. For example, in case of the NACH heuristic the lack of information on the next arrival may mean that a decision is based on its knowledge of a second or even third arrival. This kind of robustness tests is very important because many practical situations in business are characterized by the fact that only incomplete or imprecise information is available to support decision making.

Table 2: Design of the Simulation Study

Configuration *Factor*	*I: N=1, M=1*	*II: N=n, M=1*	*III: N=1, M=m*	*IV: N=n, M=m*
1. Criterion	Flow time; Cost Price	Flow time; Cost Price	Flow time; Cost Price	Flow time; Cost Price
2. Control Strategy	MBS DBH NACH MCR DJAH	MBSX NACH MCR DJAH	MBSX DJAH	MBSX DJAH
3. Interarrival Distribution	**Exponential** Uniform	**Exponential** Uniform	**Exponential** Uniform	**Exponential** Uniform
4. Quality of Information (with regard to future arrivals)	**Known**, Predicted Missing Data	**Known**, Predicted, Missing Data	**Known**, Predicted, Missing Data	**Known**, Predicted, Missing Data
5. Number of Products	1	2	1	4
6. Product Mix (%)		(**50:50**), (75:25)		(**25:25:25:25**), (50:30:10:10)
7. Capacity per product	**5**,10	(**5,5**), (7,3)	**5**,10	(**5,5,5,5**), (8,6,4,2)
8. Processing Time per product	**25**, 50	(**25,25**),(40,10)	**25**, 50	(**25,25,25,25**), (40,30,20,10)
9. Number of Machines	1	1	2	2
10.Work load	0.3;0.6;0.9	0.3;0.6;0.9	0.3;0.6;0.9	0.3;0.6;0.9
Number of Simulations	132	126	57	57

Because *workload* tends to have a major impact on the performance of a queuing system, all settings mentioned were analyzed for low (30%), moderate (60%) and high (90%) traffic intensities. While the Poisson distribution is fully defined by the mean arrival rate λ, the uniform distribution is characterized by its range. To establish a mean interarrival time $1/\lambda$ we chose the range is $[0.5/\lambda, 1.5/\lambda]$.

The performance of each heuristic was estimated using the batch means method (see e.g. Law (1991) and Hoover (1989)). The simulation horizon is 775,000 time units, which allows for 30 batches of 25,000 time units, as the first batch is discarded to account for any start up bias. Each batch corresponds to several thousands of products completed in order to guarantee that the batch means will be approximately uncorrelated. A useful tool to examine the correlation of the batches is the runs test (see e.g. Hoover (1989)). In our case, even for high traffic intensities, this test showed no significant correlation, given a significance level = 0.05. The standard deviation of the average waiting time emerging from the 30 batches is low for traffic intensities of 30 and 60% (typically in the order of 0-0.3% of the average waiting time). As may be expected standard deviation is higher for traffic intensities of 90% (in the order of 1.5% of the average waiting time). Our choice of simulation conditions is motivated by the experimental settings of Fowler (1992).

4.2 Results

In the previous subsection the design of the simulation study was discussed. Let us now consider the outcomes of the study. Results for the simulation study are summarized in Figures 2 and 3.

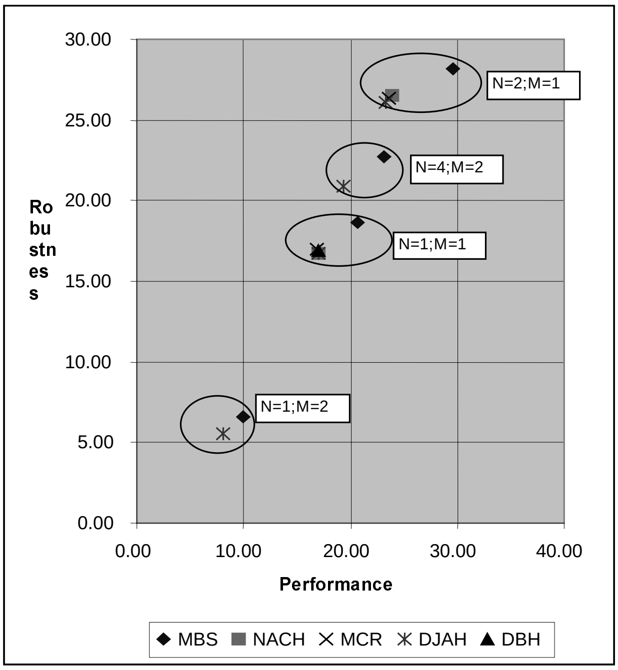

Figure 2: Comparison of Strategies – Waiting Time

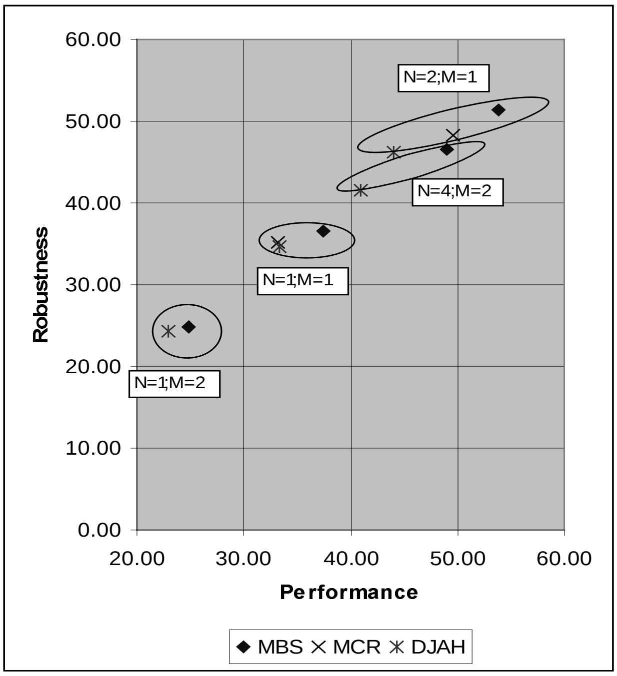

Figure 3: Comparison of Strategies – Cost Price per Item

While Figure 2 addresses settings where a flow time criterion has been adopted, Figure 3 concerns those case situations where the criterion is to minimize average cost per individual product.

Simulation results for the strategies are clustered according to a specific setting for the number of product types (N) and the number of machines (M), e.g. N=1, M=2. *Performance* is computed as the average of simulation results for settings mentioned in Table 2 for situations in which arrivals are *known* with certainty. *Robustness* is related to the response of look-ahead strategies to situations where future arrivals are forecasted or data on future arrivals are incomplete. It can be interpreted as the performance under uncertainty. Robustness is computed as the average of simulation results - concerning average waiting time and average cost price - for the corresponding case-situations mentioned in this paper. It should be remarked that results for specific settings of experimental factors can be found in Van der Zee et. al. (1997a).

Conclusions which may be drawn from the figure are:

- System performance is considerably improved if information on future arrivals is included in decision making (compare results for MBS and the look-ahead strategies)
- Simulation results for the different look-ahead strategies differ by a small margin for most settings. In case N>1 DJAH shows better performance/robustness than other look-ahead strategies.

5 EXPLORATION – MATCHING SYSTEM CHARACTERISTICS AND CONTROL STRATEGY

In Section 4 we compared look-ahead strategies for their performance. In this section we consider practical relevance of control strategies by means of an explorative simulation study. The basic question which will be addressed is: how do basic system parameters influence relative performance of look-ahead strategies? In this way we hope to draw some more general conclusions relevant for system control and design, irrespective the choice for a certain look-ahead strategy. System parameters which are studied are:

- Workload
- Lot size of arriving goods
- Number of products
- Number of machines
- Set up costs

Given the outcomes of the simulation study described in Section 4, we will only consider the DJAH and MBS strategies in this study. The following general assumptions underlie this research as far as the design of the simulation study is concerned:

- Poisson arrivals.
- Product types are identical as far as machine capacities and processing times are concerned
- Machine capacity is equal to 5.
- Processing time equals 25 time units.
- Waiting costs equal 1 per unit of time.

Note how these settings of experimental factors closely relate to the simulation study described in Section 4.

5.1 Workload

In Figure 4, average waiting time is shown for the case in which a single machine (M=1) handles one type of products (N=1). The lot size (LS) of arriving products equals one.

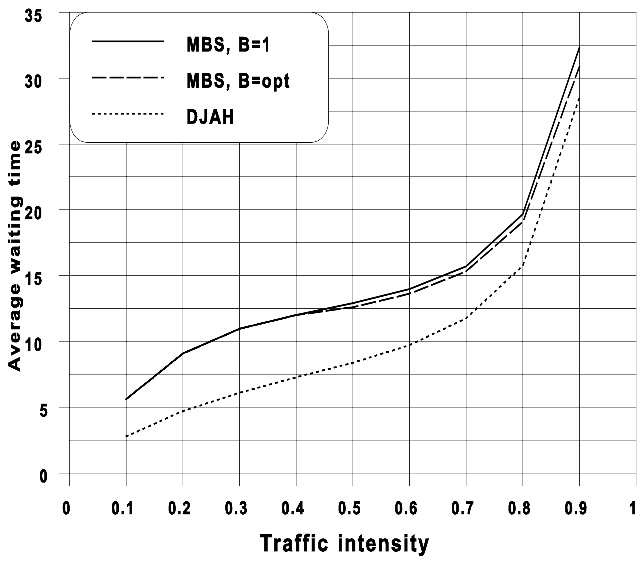

Figure 4: Workload

Figure 4 shows the results for average waiting time for DJAH and MBS for increasing workloads. Note that we relate workload to traffic intensity. Traffic intensity is defined here as the quotient of the mean arrival rate of customers and the maximum service rate of the system, cf. Chaudry et .al. (1983) and Van der Zee et. al. (1997a). Two different settings for MBS are shown in the figure:

- MBS, B=1: Glassey et. al. (1991) refer to this rule as the 'greedy' rule. According to this rule, the machine is loaded at the moment the machine is/becomes idle and there is at least one item in queue, i.e., it coincides with the MBSX rule for this case.
- MBS, B=opt: The machine is loaded only if a minimum batch size can be met by the number of items in queue. The minimum batch size is estimated by simulation in such a way that a minimal average waiting time is realized.

The figure indicates that the look-ahead strategy DJAH shows significantly lower values for average waiting time than both MBS policies. The differences tend to be greater for low and moderate traffic intensities. This can be explained by the fact that for high traffic intensities both policies will often take the same decision. The larger queue length in case of high traffic intensities will make postponement of the decision less profitable or, in case the maximum machine capacity is exceeded, even useless. These results are confirmed in earlier research by Glassey et. al. (1991,1993). Another conclusion from their research is that performance of MBS with B=1 is close to the performance of MBS with B=opt. The results in Figure 4 indicate that this proposition is true for low traffic intensities, where a minimum batch size of 1 is the optimal choice. For moderate and high traffic intensities percentual differences of 3-5% are found. In our opinion these differences are not negligible.

5.2 Compound Arrivals

In order to obtain insight in system behavior in case of compound arrivals, two series of simulations are performed. In case LS=1,2,… lot sizes of arriving products may be one or two, each with probability 1/2. In case LS=1,2,3, lot sizes of arriving products are 1, 2 or 3, each with probability 1/3. The results for these simulations are depicted in Figure 5. To enable comparison with settings in which products arrive one at a time, the results for DJAH which were found in Subsection 5.1 are included in the figure.

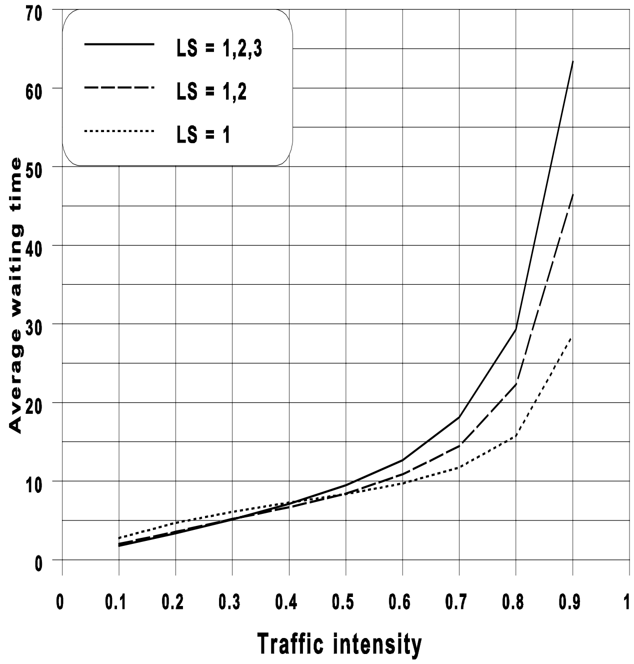

Figure 5: Compound Arrivals

The figure shows that for low traffic intensities the average waiting time for compound arrivals is smaller than for situations in which products arrive individually. This is explained by the fact that at low traffic intensities the loading of the machine is often only dependent on the next arrival moment due to the low number of arrivals. Average waiting time is therefore mainly determined by those few arrivals which take place during processing. Since in case of compound arrivals the number of arrivals decreases because of the increase in lot size, less arrivals may be expected during processing. As a consequence average waiting time reduces. On the other hand, at moderate and high traffic intensities, machine capacity gets an increasing influence on performance. The irregularity of arrival moments combined with the varying lot sizes leads to higher average waiting times. As expected, the effect is greater if the variance of lot sizes is greater.

In Table 3, the relative differences in percentages between DJAH and MBS for compound arrivals are shown for different traffic intensities (ρ).

Table 3: Relative Performance of DJAH compared with MBS

P	LS = 1		LS = 2		LS = 3	
	Δ1	Δ2	Δ1	Δ2	Δ1	Δ2
0.1	50	50	51	51	44	44
0.2	48	48	51	51	44	44
0.3	44	44	46	46	42	42
0.4	39	39	43	43	38	38
0.5	35	34	38	36	34	32
0.6	30	29	32	29	29	26
0.7	25	23	26	22	23	17
0.8	20	17	19	13	16	11
0.9	12	8	9	6	8	4

Δ1 = 100 * (MBS,B=1 - DJAH) /(MBS,B=1)
Δ2 = 100 * (MBS,B=opt - DJAH) /(MBS,B=opt)

The results in Table 3 indicate large improvements for DJAH in case of compound arrivals in comparison with MBS. Remarkably, the relative performance for DJAH improves from LS=1 to LS=1,2 for low and moderate traffic intensities, whereas it decreases for LS=1,2,3. Probably, the latter effect is due to reduction of decision options open to the controller, because of the fact that less arrivals take place as a consequence of the increased lot size. The lack of alternative decision options forces DJAH to make the same decision as MBS in more cases, which leaves less room for improvement.

5.3 Number of Products

By definition, products of different types cannot be processed together in one batch, since they require different processing conditions. This restriction on the use of a machine complicates the problem. Not only does one have to determine when to load a machine, also the type of product to be loaded has to be established. As a consequence of the larger product assortment which has to be handled, higher average waiting times are to be expected. These ideas are confirmed by a series of simulations, in which the number of product types (N) is varied. The results of these simulations are depicted in Figure 6.

Figure 6 shows the average waiting time in case DJAH is used as a control strategy. The results clearly indicate that the number of different products has a great influence on system performance. For example, the average waiting time for a system in which 10 types of products are handled is equal to about 4-10 times the average waiting time for a similar system, which handles only one type of product. Reduction of the number of products by forming product families for which processing conditions are uniform may therefore be very worthwhile in practical business situations. Of course, this implies that product specifications may have to be adapted. On the

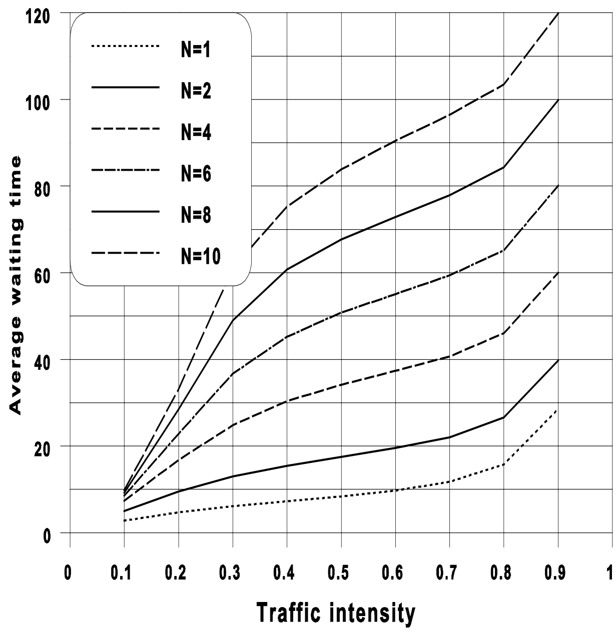

Figure 6: Number of Products

other hand, the results point out that an enlargement of the assortment should be carefully evaluated in view of its consequences on system performance.

In Table 4, the relative differences in percentages between DJAH and MBSX are shown. MBSX equals the extended MBS rule (cf. Fowler 1992). The extension is needed because the MBS rule only covers the single product case. According to this rule preference is given to the product with the longest queue length. For the setting in which only a single product type (N=1) is handled, DJAH is compared with MBS with B=opt.

Table 4: Relative Performance of DJAH compared with MBSX

P	N=1	N=2	N=4	N=6	N=8	N=10
	Δ	Δ	Δ	Δ	Δ	Δ
0.1	50	30	16	11	10	7
0.2	48	32	20	14	10	6
0.3	44	28	18	12	8	5
0.4	39	24	15	10	7	5
0.5	34	21	14	8	6	4
0.6	29	17	10	7	5	4
0.7	23	15	8	5	4	3
0.8	17	11	7	5	3	3
0.9	8	8	5	4	3	2

Δ = 100 * (MBSX,1 - DJAH) /MBSX

The results in Table 4 clearly indicate that the relative performance of DJAH decreases with increasing number of product types. This is as expected, because less profit is to be gained by postponing the loading of the machine while other product(type)s have to wait. Another conclusion is that application of DJAH as a control strategy is profitable even at a high number of product types.

5.4 Number of Machines

We will now discuss situations in which multiple machines are available. Figure 7 shows simulation results for settings where the number of machines (M) varies between 1 and 10 and DJAH is adopted as a control strategy. Note that the addition of an extra machine is accompanied by an equivalent increase in traffic intensity.

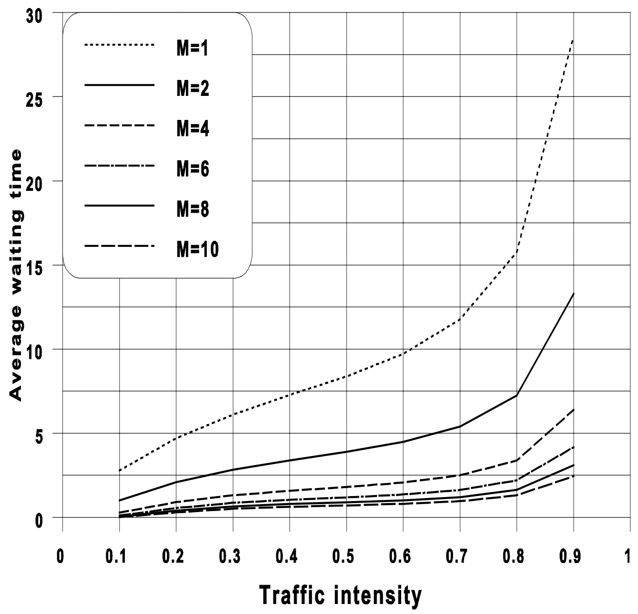

Figure 7: Number of Machines

As expected, Figure 7 shows how an increase of the number of machines leads to a reduction of average waiting time. This effect is rather strong for a low number of machines (M=2, M=4). For higher numbers of machines an effect of decreasing marginal utility is observed.

Some remarkable results are found if the performance of DJAH is compared with that of MBS (Table 5). A sharp distinction occurs between both MBS policies. Again this confirms that the proposition of Glassey (1991,1993) with regard to the near optimal performance of MBS with B=1 is not confirmed by our experiments. The simulation results indicate that relative performance of DJAH, in comparison with MBS with B=1, improves if machine numbers go up. If performance of DJAH is compared with that of the best MBS policy, a quite different effect can be recognized. While at first relative performance of DJAH improves if the number of machines goes up, for higher numbers of machines relative performance of DJAH gets worse. The latter effect is rather strong for high traffic intensities. A likely explanation is that for higher numbers of machines the influence of the stochastic character of the arrival pattern on system performance decreases, while machine availability becomes more important. As might be expected, this effect is stronger for higher traffic intensities, where the limitations on machine capacity strengthen the effect. As a consequence, less profit is to be gained by applying look-ahead strategies, which try to improve system performance mainly by their (limited) knowledge of the arrival pattern. Applying these strategies can even be counterproductive as is shown in Table 5 for a traffic intensity of 0.9 and a number of machines higher than 4. The good performance of the best MBS policy implies that in these cases it seems to be of more importance to balance machine use. This result suggests a limit for the use of look-ahead strategies. However, a few remarks are in order for a correct interpretation of this conclusion. In the first place, knowledge of the right minimum batch size is required – performance of MBS is parameter dependent (compare Subsection 5.1). A wrong choice may result in a bad system performance (e.g. compare results for MBS with B=1 and MBS with B=opt). Establishing these batch sizes might not always be a trivial task. Secondly, as long as the number of machines is not too high, the effect is limited to high traffic intensities. Thirdly, it is questionable if the effect will be evenly strong for cases in which alternative types of machines are available (Cf. Van der Zee

Table 5: Relative Performance of DJAH compared with MBS

P	M=1		M=2		M=4		M=6		M=8		M=10	
	Δ1	Δ2	Δ1	Δ2	Δ1	Δ2	Δ1	Δ2	Δ1	Δ2	Δ1	Δ2
0.1	50	50	53	53	56	56	57	57	58	58	58	58
0.2	48	48	54	54	58	58	60	60	61	61	61	61
0.3	44	44	52	52	58	51	59	51	60	47	61	45
0.4	39	39	48	44	56	46	58	45	58	43	59	42
0.5	35	34	44	40	53	42	55	41	56	40	57	38
0.6	30	29	40	35	49	39	52	39	53	38	53	37
0.7	25	23	36	30	45	31	47	29	49	28	50	27
0.8	20	17	30	19	38	16	40	12	41	8	42	5
0.9	12	8	19	7	25	1	30	-5	28	-11	29	-17

Δ1 = 100 * (MBS,B=1 - DJAH) /(MBS, B=1)
Δ2 = 100 * (MBS, B=opt - DJAH) /(MBS, B=opt)

et. al., 1999). After all, in these situations the fit between (static) machine and product characteristics becomes important. These characteristics are not included in the MBS(X) rule.

In this subsection we studied the influence of the number of machines on system performance. Examples of related research questions are:

- Would it be wise to buy a single machine or two machines with a smaller capacity ?
- Does machine grouping, i.e. reducing problem complexity by a fixed allocation of machine groups to product groups, make sense ?

Answers to suchlike questions can be found in Van der Zee (1997a,c).

5.5 Involving Other Cost Factors – Set Up Costs

In addition to the costs of waiting, logistical costs for operating batch processing systems often include other types of costs, like e.g. set up costs. DJAH allows for the inclusion of these types of costs, next to waiting costs. Here, we consider simulation results for situations where set up costs (S) equal fixed amounts 20 and 100 (see Figure 8). The other experimental settings equal those of Subsection 5.1.

Figure 8 indicates that the relative performance of DJAH is stronger for lower set up costs. This is as expected, as higher set up costs demand for a larger batch size. This leaves less room for optimization. A good calibration of the minimum batch size for MBS will therefore reduce performance differences between MBS and DJAH.

In Figure 9, it is shown how both types of costs influence the average cost price per product for S=60. The results indicate that if traffic intensity goes up set up costs per item approach S/C, i.e., the minimum set up costs per item. As such the part of average cost price made up of set up costs becomes, while waiting costs tend to rise due to the limitations set by machine capacity. Note how the curves in Figure 8 and 9 suggest optimal occupation rates at which a minimal average cost price is realized.

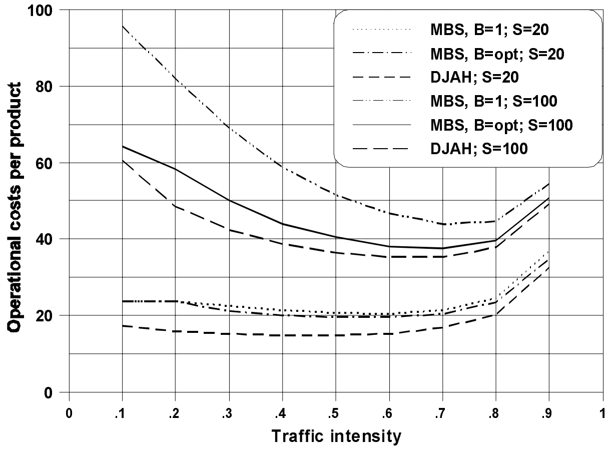

Figure 8: Logistical Costs per Item

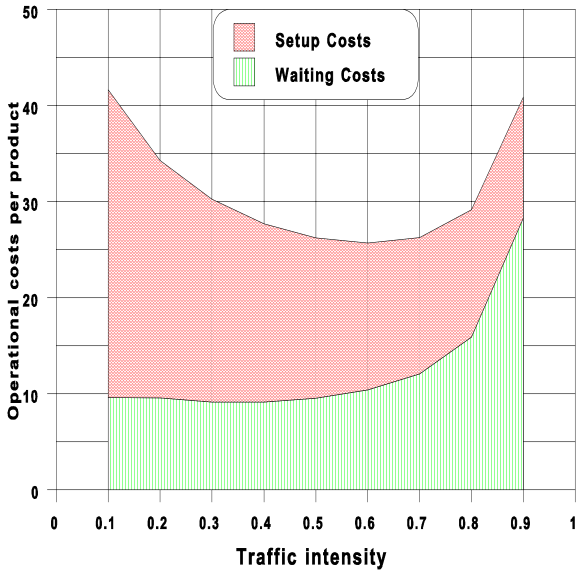

Figure 9: Logistical Costs per Item as a Function of Waiting and Set up costs

6 CONCLUSIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

In this section we will summarize our main conclusions and give recommendations for future research.

6.1 Comparison of Developed Strategies

Our simulation study indicates that:

- By making good use of just little information on future arrivals look-ahead strategies are able to improve system performance, i.e., average flow time and/or average cost price considerably.
- Although look-ahead strategies outperform the local MBS rule performance differences among rules are relatively small.
- In case the number of products (N) > 1 the DJAH rule shows better performance/robustness than other look-ahead strategies.

6.2 Exploration – Practical Use

An explorative simulation study into the practical use of look-ahead strategies relative to system control and design showed that:

- A higher *workload* reduces the profit to be gained by look-ahead strategies in comparison with MBS. This is due to the saturation effect (cf. Glassey et. al. 1993).
- For settings where *compound arrivals* take place, lower average waiting time is realized for low traffic intensities than for settings where products arrive individually. On the other hand, for moderate and high traffic intensities look-ahead strategies cannot avoid the higher average waiting time resulting from the higher irregularity of the arrival process.
- A higher *number of product types* leaves less room for look-ahead strategies to improve system performance. This is due to the fact that less profit is to be gained by postponing the loading of the machine while other product(type)s have to wait.

- The use of look-ahead strategies results in significant reductions of average waiting time for a higher *number of machines* with decreasing marginal reductions for higher machine numbers.
- Look-ahead strategies help to find an optimal trade off between the costs of waiting and set up. For higher set up costs the advantage of look-ahead strategies over MBS diminishes. This is a logical consequence of batch size becoming the important parameter to control.

6.3 Recommendations for Future Research

Several interesting suggestions for future research on look-ahead strategies for batch shop control can be given, which relate to:

- *Different system characteristics*, compare e.g. Glassey et al. (1993) who study re-entry flows in batch shop environments). Other extensions relating to practical situations are the limitation of buffer capacity, the possibility of machine breakdowns, the forming of families of product groups with different capacity requirements per unit of product and quality constraints.
- *Other cost structures/performance criteria*. Other types of costs are sequence-dependent set up costs and penalty costs for late deliveries. Alternative performance criteria may be based on due date settings or possibilities to prioritize the processing of certain products (for example because they are needed urgently elsewhere).

While the above suggestions focus on the construction of rules it is also important to direct more efforts to applied research in this context. In this way the practical validity of several extensions can be tested and benefits of the new rules may be exploited to a greater extent.

REFERENCES

Bagchi, T.P., and J.C.G. Templeton.1972. "Numerical Methods in Markov Chains and Bulk Queues", Lecture Notes in Economics and Mathematical Systems, ed. M. Beckmann, G. Goos and H.P. Künzi, 72, Berlin: Springer Verlag.

Bakkenist, 1994, Simulation tool Expect.

Booch, G. 1994. *Object-Oriented Analysis and Design - With Applications*, Redwood City: Benjamin Cummings.

Chaudry, M.L., and J.G.C. Templeton. 1983. "A First Course in Bulk Queues", New York: Wiley.

Deb, R.K., R.F. Serfozo. 1973. "Optimal Control of Batch Service Queues". *Advances in Applied Probability* 5:340-361.

Fowler, J.W., G.L. Hogg, and D.T. Phillips. 1992. "Control of Multiproduct Bulk Service Diffusion/Oxidation Processes". *IIE Transactions* 24(4):84-96.

Glassey, C.R., and W.W. Weng. 1991. "Dynamic Batching Heuristic for Simultaneous Processing". *IEEE Transactions on Semiconductor Manufacturing* 4(2):77-82.

Glassey, C.R., F. Markgraf, and H. Fromm. 1993. "Real Time Scheduling of Batch Operations", in: Optimization in Industry: mathematical programming and modeling techniques in practice, edited by T.A. Ciriani and R.C. Leachman, Wiley, Chichester, 113-137.

Hodes, B., B. Schoonhoven, and R. Swart. 1992. *Technical Report: On Line Planning van Ovens* (in Dutch), School of Management Studies, University of Twente, The Netherlands.

Hopp, W.J., and M.L. Spearman. 1996. *Factory Physics – Foundations of Manufacturing Management*, Chigago : Irwin.

Neuts, M.F.1967. "A General Class of Bulk Queues with Poisson Input". *Annals of Mathematical Statistics* 38(3):759-770.

Robinson, J.K., J.W. Fowler, and J.F. Bard. 1995. "The Use of Upstream and Downstream Information in Scheduling Semiconductor Batch Operations". *International Journal of Production Research* 33(7):1849-1869.

Uzsoy, R., C.Y. Lee, and L.A. Martin-Vega. 1992. "A Review of Production Planning and Scheduling Models in the Semiconductor Industry, Part I: System Characteristics, Performance Evaluation and Production Planning". *IIE Transactions* 24(4):47-60.

Uzsoy, R., C.Y. Lee, and L.A. Martin-Vega. 1994. "A Review of Production Planning and Scheduling Models in the Semiconductor Industry", Part II: Shop-floor Control. *IIE Transactions* 26(5):44-55.

Weng, W.W., and R.C. Leachman. 1993. "An Improved Methodology for Real-time Production Decisions at Batch-process Work Stations". *IEEE Transactions on Semiconductor Manufacturing* 6(3):219-225.

Zee, D.J. van der, A. van Harten, and P.C. Schuur. 1996. Dynamic Job Assignment Heuristics for Multi-Server Batch Operations. *Proceedings of the Second International Conference on Computer Integrated Manufacturing in the Process Industries*, ed. J.C. Fransoo, W.G.M.M. Rutten, 558-573. Research Institute BETA, Eindhoven, The Netherlands.

Zee, D.J. van der, A. van Harten, and P.C. Schuur. 1997a. Dynamic Job Assignment Heuristics for Multi-Server Batch Operations - A Cost-Based Approach. *International Journal of Production Research* 35(11), 3063-3093.

Zee, D.J. van der. 1997b. Simulation as a Tool for Logistics Management. PhD Dissertation, Faculty of Technology and Management, Department of Management–Science and Logistics, University of Twente, The Netherlands.

Zee, D.J. van der, A. van Harten, and P.C. Schuur. 1997c. Dynamic scheduling of Batch Operations with Non-Identical Machines, Technical Report p4, BETA, University of Eindhoven, The Netherlands.

Zee, D.J. van der, A. van Harten, and P.C. Schuur. 1999. On-Line Scheduling of Multi-Server Batch Operations, Technical Report 99A52, SOM, University of Groningen, The Netherlands.