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USING ORDER ROUTING SPECIFIC FLOW TIME AND WORKLOAD INFORMATION TO IMPROVE LEAD TIME AND DUE DATE PERFORMANCE IN JOB SHOPS

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Abstract

Research on due date setting in job shop production systems has revealed a number of factors that, when taken into account in order due date setting, lead to better due date performance. These factors are the processing times of the order, the number of operations of the order, and the workload in the shop at the arrival time of the order. In this paper we investigate further refinements of the way in which these factors are taken into account when setting due dates. In particular we investigate the use of complete information about the order flow time probability density function and the workload on the routing of an order.

1. Introduction

In view of the management literature, which reports the strategic importance of short and reliable lead times (see e.g. Stalk and Hout [1990]), it is plausible to assume that Sales Departments operate in a reward and penalty structure. On the one hand a cost penalty might be incurred as a function of the length of the quoted job lead-time and, on the other hand, a cost penalty might be incurred as a function of the tardiness of the job. So the firm, in some way or another, is penalized for assigning long order lead times. This penalty decreases by assigning short lead times. Also it is assumed that the firm is penalized for late deliveries.

In this paper we study a job shop where customer orders arrive dynamically over time, each order is assigned a due date upon arrival, the order is immediately released to the shop floor and processed according to its production routing after which the order is completed. The job shop consists of a number of functionally organized work centers where the orders compete for capacity. We assume that the job shop operates in a market that penalizes both long quoted lead times and late deliveries.

The due date performance of a job shop is influenced both by the shop floor control system, in particular the priority rules used at the work centers, and by the due date assignment system. There is a long history of research in both areas (for an overview see Cheng and Gupta [1989]) and also the interaction between the shop floor control system and the due date assignment system has been studied extensively (see e.g. Conway et al. [1967], Eilon and Chowdhurry [1976], Baker and Bertrand [1981], Bertrand [1983], Baker [1984], Cheng [1988], Salegna [1990] Enns [1994,1995] and Van Ooijen and Bertrand [2001]). This research has shown that the due date performance is improved if due dates are based on information about order processing times, order routing, and workload in the shop.

In this paper we build on the results of this previous research and investigate whether the due date performance can be further improved by using detailed routing and workload related information about the order. We start with investigating the relationship between the order flow time and the total workload in the shop, and the relationship between the order flow time and the workload at the work centers visited by the order, at the arrival time of the order. Then we develop customer order due date assignment policies that take into account knowledge about the order flow time probability density function as a function of the number of work center visits and the workload in the work centers visited. The due date performance that can be obtained with these policies is investigated with systematic computer simulation of a job shop model. As performance measures we use the quoted lead times, the costs and the average tardiness of the orders. The investigations are carried out for three different shop floor priority rules. The results show that, depending on the shop floor priority rule used, the new policies can improve the due date performance of a shop.

The rest of this paper is organized as follows. In Section 2 we give a short overview of recent related literature, showing what due date assignment policies have been investigated. In Section 3 we present the new customer due date assignment policy, using order flow time p.d.f.'s and workload information if the First-Come-First-Served sequencing rule is used o the shop floor. Section 4 presents the experimental design and the results of the simulation study. Since in many production environments other sequencing rules are used, the sensitivity of the performance of our policy is investigated in Section 5. Finally, in Section 6, the conclusions are given.

2. Literature review

In this section we review recent research, which focuses on improving lead-time and delivery performance in job shops with emphasis on research that uses economic performance measures.
Weeks [1978], and Seidmann and Smith [1981], present a methodology for finding the optimal planned lead time, which is defined as that lead time which results in the minimum costs associated with order lateness, order earliness, and order lead time length. They develop a due date assignment policy that minimizes the expected aggregate cost per job subject to restrictive assumptions on the priority discipline and the penalty functions. The penalty functions used are none-linear functions of the order lead-time, the tardiness and the earliness.
Vig and Dooley [1993] develop a flow time prediction model that incorporates both static and dynamic flow time estimates. The flow time they use is a weighted average of static and a dynamic estimate of the flow time. Compared to existing dynamic flow time estimation models, using a combined static and dynamic job flow time estimation method reduces average lateness and fraction tardy jobs.
Enns [1994] gives a method for setting due dates such that the percentage of tardy jobs delivered is controlled. It is based on a dynamic method of estimating prediction error variance. In succeeding research, Enns [1995] presents a forecasting approach to flow time prediction in a job shop. The flow time prediction relationship developed considers both job characteristics and shop loading information. The estimated distribution of forecast error is used to set delivery safety allowances, which are based on a desired level of delivery performance.
Lawrence [1995] investigated the performance of flow time estimator method that consist of two parts. The first part estimates the average flow time, $\overline{f_i}$, of an arriving order; the second part estimates the parameters of the distribution function of the flow time estimation error ε_i . Then the true flow time of an order can be characterized at the arrival of the order as: $f_i = \overline{f_i} + \varepsilon_i$. The flow time estimation error distribution function is approximated by using the Ramberg-Schmeiser distribution. For a given way of estimating the average flow time, $\overline{f_i}$, the estimation error distribution function is fitted using empirical data from computer simulations of a job shop model.
Bertrand and Van Ooijen [1997] and Van Ooijen and Bertrand [2001] obtained very good results with flow time estimators based on empirically determined order flow time statistics per job category, where jobs are categorized according to the routing length. The order flow time statistics suggest that the shape of the flow time distribution function strongly depends on the number of operations in a job, and on the sequencing rule used at the work centers.
In Sabuncuoglu and Comlekci [2002] a method is developed for estimating the job flow times in a dynamic job shop environment using detailed job, shop and route information for each operation of a job. The method considers explicitly the machine imbalance information in the estimation process. This study shows that using regression analysis, taking into account the shop load, leads to a rather good prediction of the flow time. The regression analysis is done on empirical data.

All research referred to above either seeks to improve the predictability of the order flow time in the shop, or uses information about the order flow time to achieve a better performance in the market place. The results indicate that using more information about the orders and about the shop load, may improve the lead-time and due date performance.
In this research we again use order flow time statistics, as in Van Ooijen and Bertrand [2001], and increase the level of detail in the order and shop information used for setting order due dates and investigate the performance improvement obtained for various economic settings and various shop

floor control rules. In the next section we present our customer order due date setting method in more detail.

3. Customer order due date assignment

In this paper we focus on assigning customer order due dates for production environments that can be characterized as job-shops. The approach taken is that we base the customer order due date on knowledge about the order flow time statistics. As in Sabuncuoglu and Comlekci [2002] this knowledge can be obtained from historical data or from simulation. Knowledge about the order flow time can be available at different levels of detail. For instance, we could use an aggregate order flow time distribution function, which represents the flow time of an arbitrary order that arrives at an arbitrary moment. Such a distribution function could be determined by applying queueing theory to a model of the shop and the order arrival process. However, this aggregate flow time distribution function would neglect information about the particular characteristics of each order such as the order routing and the order processing time, and information about the orders present in the shop that is available at the arrival time of the order. Previous research (Conway et al. [1960], Bertrand [1983], Enns [1990], Enns [1995]) has shown that using this information can substantially improve the due date performance. In all this research, knowledge about the order and the shop was used to better estimate either the expected value of the individual order lead-time or the variance in the lateness of the individual order.

Knowledge about the order flow time can also be available in more detail, for instance, instead of an aggregate order flow time distribution function, order flow time distribution functions might be known for a number of categories. Previous research (Van Ooijen and Bertrand [2001]) has shown that the order flow time statistics of orders with the same routing length contains valuable information for assigning customer order due dates. Basing the customer order due date on these statistics substantially improves the due date performance over that of policies that base customer order due dates only on estimates of the mean order flow time and the variance of the lateness.

Previous research has also shown that the total workload in the shop at the arrival time of an order is a good predictor of the order flow time (Bertrand [1983], Enns [1994,1995], Van Ooijen and Bertrand [2001]). However, the quality of the total workload as a predictor of the order flow time may be different for orders with different routing length. Since the total workload is an aggregate measure we may expect it to perform better as a predictor for orders with many operations than for orders with few operations. For instance, for an order with only one operation, the main determinant of the flow time will be the number of orders in the queue of the particular work center it will visit. This number is part of the total workload, but for a five-work center shop the total workload (the number of orders in the shop) will be only loosely related to the workload in any of the constituting work centers.
We have investigated the predictor performance of the total workload for different order routing length by performing a regression analysis between realized order flow time and the total workload at the arrival time of the order. For this investigation we performed a simulation study of a job-shop with the following characteristics:

- The job-shop model consists of five single machine work centers (as in many research of this type, see Conway et al. [1967]).
- Orders arrive according to a Poisson process. We assume that the delivery performance has no influence on the arrival rate. So, customers do not have a memory with regard to the past performance of the shop.
- Order routings are determined upon arrival. The routings are generated in such a way that each work center has an equal probability of being selected as the first work center. After the first operation the probabilities of going to any of the other work centers are equal and depend on the probability of leaving the shop, which in turn depends on the average routing length. We have used an average routing length of 5, so the probability of leaving the shop after each completed operation is 0.2, and the work center transition probabilities all equal 0.8/4=0.2.

FCFS	g	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
O	r^2	0.18	0.34	0.45	0.52	0.57	0.60	0.64	0.67	0.67	0.67	0.65	0.68	0.67	0.69	0.66
	c	1.10	2.29	3.52	5.12	6.07	7.85	8.95	11.52	14.07	17.60	19.44	18.54	26.29	24.44	27.49
	a	0.20	0.39	0.58	0.77	0.97	1.15	1.35	1.52	1.67	1.82	2.01	2.27	2.29	2.56	2.69
	ó$_e^2$	86	132	187	247	317	390	474	543	623	717	969	1091	1136	1401	1372
W	r^2	0.91	0.85	0.84	0.82	0.81	0.80	0.81	0.80	0.78	0.76	0.77	0.77	0.74	0.76	0.73
	c	0.83	2.14	4.05	5.94	7.76	9.90	11.97	14.84	17.68	20.05	22.05	24.70	29.02	31.23	29.12
	a	1.00	0.99	0.95	0.93	0.93	0.92	0.91	0.90	0.88	0.89	0.89	0.89	0.86	0.86	0.88
	ó$_e^2$	10	29	56	93	142	192	248	333	415	525	647	806	923	1094	1108

Table 1. Results of the regression analysis of the flow time per order category, versus the overall or work center workload; orders are processed according to First Come First Served at each work center. **O**: the model used is: tpt = c +a*workload + error; workload is measured as the total number of orders in the shop at the arrival time of the order. **W**: the model used is: tpt = c +a*workload + error; work load is measured as the number of orders in the work centers on the routing of the order at the arrival time of the order

- At each work center processing times are generated from a negative exponential probability density function with a mean value of one time unit. Set-up times and transportation times are considered to be zero.
- The mean value of the order inter-arrival time is equal to 10/9, which implies a machine utilization rate of 90%.
- First Come First Served sequencing at the work centers.

Table 1 (FCFS; **O**) gives the results of a regression analysis of the average order flow time and the work load in the shop, per categories of orders with equal routing length, g. The data in Table 1 clearly show that the predictor performance, measured by r^2 and ó$_e^2$, depends on the order routing length. For short routings, the prediction performance is quite poor (r^2 ranges from 0.18 to 0.52) whereas for large routings the prediction performance is quite good (r^2 up to 0.70).
These results suggest that prediction performance can be improved by only considering the workload in the work centers at the routing of an order (instead of the total workload). To test this idea we have performed a regression analysis between average order flow time per category and the total number of orders in the work centers on the routing of an order. The row **W** in Table 1 presents the results. These results provide strong support for our conjecture. The results show that the total number of orders on the routing of a work order is a very strong predictor of the average order flow time; in particular for orders with a few operations r^2 is much larger and ó$_e^2$ is much smaller than with the total aggregate work load as a predictor; however, also for orders with many operations r^2 is larger and ó$_e^2$ is smaller.

The next question is how to exploit the strong predicting power of the total number of orders on the routing of an order for assigning customer order due dates. In a previous paper, Van Ooijen and Bertrand [2001] corporated total workload information in empirically constructed waiting time distribution functions per order category of what they called the normalized waiting time:

$$w_j^J = \frac{J}{J_j} w_j$$

where J = the long term average number of order in the shop
J_j = the number of orders in the shop at the arrival of order j

The empirically constructed distribution functions where successfully used to assign predictable customer order due dates per category.

In this study we incorporate routing related workload information in empirically constructed normalized waiting time distribution functions per order category using:

$$w_j^{\,q} = \frac{q}{q_j + 1} w_j$$

where q = the long term average number of orders at the work centers on the routing of an order

q_j = the actual number of orders in the work centers on the routing of order j at the arrival time of order j

We assign customer order due dates using these empirically constructed order waiting time distribution function.

The benefits from using routing related work load information for customer order due date assignment are investigated in the setting where an order incurs a lead time related cost equal to the length of the lead time assigned to that order, and a tardiness cost equal to c times the amount of time the order is tardy.

In the next section we present the simulation study that has been performed to investigate the effects of using routing related work load information for customer order order due date setting under the FCFS sequencing rule on the shop floor.

4. The experimental design and results

We assume that in the market there is an accepted order lead time *m*. Quoting a lead time shorter than *m* does not give any benefit. Quoting a lead time longer than *m* results in a reduction of the order revenue proportional to the lead-time minus *m*. We model this price component as a linear function:

$p(l_j) = a$ $0 \; l_j \; m$

$p(l_j) = a - b(l_j - m)$ $l_j \; m$

where l_j : lead time of order j

p(.) : the part of the order revenue that depends on the lead-time

m : the lead-time that is generally accepted by the market

a,b : constants

If an order is completed later than its customer due date, the job is tardy and a tardiness cost *c* is incurred for each unit tardy. Without loss of generality we assume that *m* equals 0.

Using the total work load information the customer order due date for an order *j* of category *g* is assigned as:

- $$d_j = r_j + \sum_i p_{ji} + \frac{J_j}{J} H_g^{\,J\leftarrow}(\alpha) \qquad (1)$$

where H_g^J (á) denotes the workload normalized waiting time distribution function of the order category *g* and α is the fraction of orders that are on time.

Using routing related work load information the customer order due date for an order of category *g* is assigned as:

- $$d_j = r_j + \sum_i p_{ji} + \frac{q_j}{q} H_g^{\,q\leftarrow}(\alpha) \qquad (2)$$

where H_g^q (á) denotes the routing-workload normalized waiting time of the order category *g*.

As a benchmark for evaluating the performance that can be obtained from using total work load or routing work load information, we have also established the due date performance that results from basing customer order due dates on non-normalized empirically constructed waiting time distribution functions per category *g*, $H_g(.)$

In this case the customer order due dates are assigned as:

- $$d_j = r_j + \sum_i p_{ji} + H_g^{\leftarrow}(\alpha) \qquad (3)$$

G		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	C
50%	N	17	31	44	57	70	83	97	110	123	136	149	162	175	188	201	63
	T	16	29	40	51	63	74	86	97	109	120	132	144	155	167	179	57
	R	12	24	36	47	59	71	82	94	106	118	130	142	154	165	177	53
90%	N	33	51	70	89	108	126	146	164	183	201	220	238	256	275	292	97
	T	28	40	54	68	82	96	110	124	139	153	168	183	198	213	229	75
	R	16	31	46	61	75	90	106	121	136	151	167	183	198	215	230	68
95%	N	40	59	81	102	123	144	166	187	208	227	249	269	289	310	328	112
	T	32	44	60	75	89	105	120	135	151	167	183	201	217	234	251	83
	R	18	36	52	68	84	101	117	134	150	167	185	203	220	238	255	76

Table 2. The total costs, C_g, for each of the three due date setting policies and three on time service levels for the FCFS sequencing rule; N=non-normalized policy, T=total workload policy, R=routing related workload policy; C=average cost

For all the three due date setting policies, non-normalized (N), total work load normalized (T) and routing work load normalized (R), simulation experiments have been performed where optimal customer order due dates have been determined for three values of the on-time service level: 0.50, 0.90 and 0.95.

The performance is measured as the sum of due date related costs and tardiness related costs according to:

$$C_g = \sum_{j=1}^{N} (b.l_{j,g} + c.T_{j,g})$$

where b = lead time costs per unit lead time
c = tardiness costs per unit tardy
$T_{j,g}$ = max (0, $f_{j,g}$-$l_{j,g}$)
$f_{j,g}$ = flow time of order j of category g
$l_{j,g}$ = $d_j - r_j$ = lead time of order j of category g

Like in Sabuncuoglu and Comlekci [2002], we carried out two sets of simulation experiments. With the first set we determined the non-normalized, the total workload normalized and routing related workload normalized order waiting time distribution functions per category. Next we performed a set of experiments to investigate the performance of the system if the distribution functions, constructed in the first set of experiments, are used for setting the customer order due dates. Each measurement results from 10 simulation runs, with order streams that differ from the order streams that were used to construct the waiting time distribution functions. The common random number technique was used to reduce the variance between experiments with different settings.

Table 2 shows the cost performance obtained with the FCFS priority rule for the non-normalized policy (N), the total workload normalized order waiting time policy (T) and the routing related workload normalized waiting time policy (R). The column C gives the average (arrival rate weighted) cost performance. For each category, each due date setting rule and each on-time service level, the actual on-time performance was very close to the on-time target, implying a very high performance control at the category level.
Under FCFS sequencing, the due date policies T and R outperform the policy N. The routing related workload policy R, outperforms the total workload policy T for almost all categories. Only for on-time targets of 0.90 or 0.95 and long routings the costs with policy R are about the same, or even a bit higher than with the policy T.

5. Sensitivity of the performance of the customer order due date assignment policy to the shop floor control system

In many production situations a priority rule is used that aims at achieving short order flow times or high due date reliability. Therefore we also investigated the situation where the Operation Start Date rule (OSD) and the Modified Operation Due date rule (MOD) is used on the shop floor. OSD has been shown to produce a small variance in lateness (Kanet and Hayya [1982]) and MOD effectively combined the flow time reducing properties of Shortest Processing Time (SPT) with the lateness reducing properties of OSD (Baker and Bertrand [1981]). These priority rules operate on internal operation due dates.

Internal operation due dates have been set according to the following rules: For the situation where customer order due dates are based on total workload, the internal due dates have been set as:

$$OD_{j,i} = r_j + \sum_{k=1}^{i} (p_{j,k} + \beta_{j,k}^{r_i}) \tag{4}$$

where $OD_{j,i}$: the operation due date of operation i of order j
r_j : the arrival time of order j
$p_{j,k}$: the processing time of the k-th operation in the routing of order j

and $\beta_{j,k}^{r_j}$ equal to:

$$[\frac{J(r_j).p}{m.\rho} - p]$$

where $J(r_j)$ = the number of order in the shop at time r_j
p = average operation processing time
m = number of machines in the shop
ñ = steady state utilization rate of the shop

For the situation where customer order due dates are based on routing related work load, the internal due dates are set according to

$$OD_{j,i} = r_j + \sum_{k=1}^{i} (p_{j,k} + \beta_{j,k}^{r_i})$$

with $\beta_{j,k}^{r_j}$ equal to:

$$p.q_k^{r_j}$$

where $q_k^{r_j}$ = the number of orders waiting in the queue at the work center of the k-th operation of order j, at the arrival time of the order.

We first we performed a regression analysis of the relationship between mean average order flow time per category and work load for these shop floor control systems. The results of this analysis are given in Table 3 for the OSD rule and in Table 4 for the MOD rule.

The data in Table 3 clearly show that under OSD sequencing the predicting performance of the total workload, measured by r^2 and σ^2, depends on the order routing length. For short routings, the prediction performance of the total workload is poor (r^2 ranges from 0.14 to 0.69) whereas for long routings the prediction performance of the overall workload is quite good (r^2 up to 0.96). However, with routing related workload information, the predicting performance is quite high, also for orders with short routings; r^2 ranges from 0.82 for orders with one operation to 0.96 for orders with 15 operations.

Under MOD sequencing, the dependence of prediction performance on routing length is much weaker. The advantage of MOD sequencing of course is the decrease in mean order flow time that can be achieved relative to FCFS or OSD sequencing. However, the data in the Table 4 show that this may go

OSD	G	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	r^2	0.14	0.37	0.56	0.69	0.78	0.82	0.87	0.90	0.91	0.92	0.92	0.94	0.95	0.94	0.96
O	C	1.64	1.87	2.59	3.31	3.00	4.03	4.16	4.57	5.86	6.41	7.60	7.40	7.19	7.70	5.91
	A	0.17	0.40	0.61	0.82	1.05	1.24	1.47	1.67	1.86	2.09	2.27	2.50	2.73	2.94	3.21
	ó$_e^2$	82	120	130	134	138	146	150	150	157	157	191	180	163	250	167
	r^2	0.82	0.83	0.87	0.89	0.91	0.92	0.94	0.94	0.95	0.95	0.96	0.96	0.96	0.97	0.96
W	C	0.19	1.06	2.20	3.26	4.64	5.73	7.03	7.93	9.45	10.98	11.48	12.68	13.34	14.53	16.49
	A	1.13	1.08	1.04	1.02	1.00	0.99	0.99	0.99	0.98	0.98	0.98	0.98	0.98	0.98	0.97
	ó$_e^2$	26	42	51	59	70	74	86	93	101	101	114	124	122	145	145

Table 3. Results of the regression analysis of flow time versus overall or work center workload when the OSD sequencing rule is used; **O**: the model used is: tpt = c +a*workload + error and work load is measured as the total number of orders in the shop at the arrival time of the order and for the setting of the operation due dates $\beta_{j,k}^{r_j}$ is based on the overall workload. **W**: the model used is: tpt = c +a*workload + error and work load is measured as the number of orders in the work centers on the routing of the order at the arrival of the order and for the setting of the operation due dates $\beta_{j,k}^{r_j}$ is based on the order related workload.

MOD	g	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	r^2	0.04	0.12	0.17	0.27	0.34	0.29	0.55	0.51	0.54	0.56	0.52	0.36	0.58	0.68	0.66
O	c	1.39	2.04	2.17	2.50	2.97	2.63	6.01	5.23	7.17	6.67	6.45	3.03	7.51	11.87	13.60
	a	0.13	0.33	0.57	0.79	1.01	1.27	1.37	1.64	1.81	2.08	2.30	2.73	2.71	2.84	2.99
	ó$_e^2$	93	182	367	410	481	916	376	629	680	783	1161	3155	1288	963	974
	r^2	0.58	0.64	0.63	0.68	0.74	0.79	0.87	0.79	0.86	0.81	0.78	0.76	0.79	0.89	0.89
W	c	0.15	0.67	1.45	2.43	3.07	4.24	6.02	7.63	8.94	9.32	8.33	9.88	11.27	14.92	16.45
	a	1.01	1.01	1.02	1.01	1.01	1.01	0.99	0.98	0.98	1.00	1.02	1.02	1.00	0.98	0.97
	ó$_e^2$	41	64	119	145	161	168	128	259	184	316	524	726	573	373	320

Table 4. Results of the regression analysis of flow time versus overall or work center workload when the MOD sequencing rule is used; **O**: the model used is: tpt = c +a*workload + error and work load is measured as the total number of orders in the shop at the arrival of the order and for the setting of the operation due dates $\beta_{j,k}^{r_j}$ is based on the overall workload. **W**: the model used is: tpt = c +a*workload + error and work load is measured as the number of orders in the work centers on the routing of the order at the arrival of the order and for the setting of the operation due dates $\beta_{j,k}^{r_j}$ is based on the routing related workload.

at the cost of a decrease in the predictability of the order flow times. Nevertheless, the predicting performance of routing related workload information is still quite good.

We next have repeated the simulation experiments with the three due date assignment policies under OSD and MOD and measured the total costs for three on-time target service levels: 0.50, 0.90 and 0.95. Again, for each of the experiments and for each order category the realized on-time performance was very close to the target, which demonstrates the high controllability of the performance that can be obtained with the use of empirically constructed flow time distribution functions.
The Tables 5 and 6 give the total costs per category, and the overall costs, for the three on-time target service levels for each of the three policies N, T and R, under the shop floor rule OSD and MOD respectively.
Under OSD the due date policies T and R outperform N, and the routing work load related policy R outperforms the total workload policy T, showing that the ordering in performance obtained under FCFS sequencing also applies under OSD sequencing.
Also under MOD the policies T and R clearly outperform policy N. However, the ordering of the policies T and R is not so straightforward. For an on-time target service level of 0.50, the total work load policy T outperforms the routing related work load policy R, whereas for target levels 0.90 and 0.95 R outperforms T. Apparently, the mixing of SPT and OSD sequencing under MOD creates a less predictable order flow time, as was shown in the regression analysis. As a result the advantage of

g		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	C
50%	N	21	36	48	59	69	80	90	100	110	120	131	141	151	162	171	62
	T	16	28	38	48	58	69	78	88	98	108	119	129	139	149	159	52
	R	15	26	36	46	56	66	76	86	96	106	116	126	136	146	156	50
90%	N	51	69	82	93	104	114	125	135	145	155	166	175	186	196	206	95
	T	27	39	49	59	69	80	90	100	110	120	130	140	151	160	170	63
	R	20	33	44	55	65	76	86	96	106	116	127	137	147	157	167	58
95%	N	65	83	96	107	117	128	139	149	159	169	180	190	200	210	219	109
	T	31	43	53	63	74	84	94	104	114	124	135	144	155	165	175	68
	R	24	38	49	60	70	80	90	101	111	121	131	142	153	163	172	63

Table 5. The total costs, C_g, for each of the three due date setting policies and three on time service levels for the OSD sequencing rule; N=non-normalized policy, T=total workload policy, R=routing related workload policy; C=average cost

G		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	C
50%	N	8	18	29	40	51	62	73	83	94	105	115	126	137	147	158	45
	T	9	17	25	33	41	49	57	64	72	80	88	96	103	111	118	36
	R	11	19	28	36	45	53	62	70	78	87	96	104	112	121	129	40
90%	N	18	33	47	62	75	89	103	115	129	142	153	167	181	192	205	67
	T	17	30	42	54	65	75	86	96	106	116	125	134	145	154	163	57
	R	15	27	38	49	59	69	78	88	97	106	116	125	135	143	152	52
95%	N	25	45	63	82	100	117	134	149	166	183	195	211	229	241	256	87
	T	26	44	59	75	89	102	116	127	139	152	162	173	187	197	207	77
	R	21	36	49	61	72	83	94	105	115	125	136	145	156	166	175	64

Table 6. The total costs, C_g, for each of the three due date setting policies and three on time service levels for the MOD sequencing rule; N=non-normalized policy, T=total workload policy, R=routing related workload policy; C=average cost

having shorter average flow times is offset by a high variance in the flow time and a weaker relationship between the flow time of an order and the workload in the shop at its arrival time. The negative effects of this on the performance are demonstrated by the fact that for 0.95 on-time target, the total costs under MOD (Table 6) are larger than under OSD (Table 5), if workload related due date policies are used.

6. Conclusions

In this paper we have investigated the possible contribution to due date performance in job shops, of using detailed information about the workload in the work centers on the routing of an order, when setting the customer order due date of the order. We have used computer simulation of a job shop model to compare the order flow time prediction performance of both the total workload and the routing related workload at the arrival time of an order. Regression analysis showed that, independent of the number of operations of an order, the routing related workload is a better predictor of order flow time than the total workload; in particular for short orders, that is orders with only a few operations, the flow time predictor performance is much better. Building on this model, we have developed due date assignment policies based on empirically constructed normalized order waiting time distribution functions per order category. Normalization in fact uses either the total workload or the routing related workload and orders are categorized according to the number of operations. Simulation experiments with these policies for a five-work center job shop under First Come First Served sequencing at the work centers shows that the due date policy that exploits information about the workload in the work centers on the routing of an order, almost consistently outperforms the policy that uses total workload information.

To test the sensitivity of the results for the type of shop floor control system used, we have extended the research to job shops with Operation Start Date sequencing and Modified Operation Due date sequencing. The results show that under OSD the result is even stronger: the policy that uses routing related workload information consistently outperforms the policy that uses total workload. Under MOD sequencing, the results are less clear: Mod sequencing clearly distorts the regular flow of the orders, thereby decreasing the predictability of the flow. However, for high on-time service level targets, the policy that uses routing related workload information still outperforms the policy that uses total workload.

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