Learning and Labor Assignment in a Dual Resource Constrained Cellular Shop

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ABSTRACT

Shops employing cellular manufacturing consciously sacrifice the flexibility of providing parts with multiple routings for the efficiencies of processing families of similar parts on machines dedicated to their requirements. This tradeoff can however limit shop performance. Substantial gains in efficiency are required to offset the adverse impact of even modest decreases in routing flexibility. Manufacturing cells exploit teamwork and repetition that can yield such gains in efficiency. Recent studies have shown that in a cellular shop that benefits from learning through repetitive processing, limitations attributable to routing flexibility can be more than offset. Moreover, the shop can respond more quickly to changes in demand than a job shop. This study examines the impact of labor assignments in a dual constrained cellular shop in which processing times decrease with operator task repetition. Results indicate that in the presence of operator learning, shop performance is significantly affected by the flexibility permitted in labor assignments. Moreover, the sensitivity of performance to labor assignments is significantly impacted by the tightness of the labor constraint and on the magnitude of learning effects.

Key Words: Cellular Manufacturing, Group Technology, Learning Curve, Simulation

1. INTRODUCTION

Cellular manufacturing is a manufacturing configuration commonly used by batch manufacturers to improve competitiveness and responsiveness. Dedicating and co-locating machines used to produce a family of products allows setup frequency to be reduced, material flow to be improved, and product quality to be increased. These outcomes have been validated by evidence from industry (Wemmerlov & Hyer, 1989, Wemmerlov & Johnson, 1997). In contrast, several academic studies have shown that manufacturing cells are hindered by their limited routing flexibility, and, as a result, may perform poorly when compared to job shops organized by machine function (Flynn & Jacobs, 1987, Morris & Tersine, 1990, Suresh, 1992, Suresh & Meredith, 1994, Jensen et al., 1996, Kannan & Ghosh, 1996). These limitations can however be effectively managed by for example exploiting reductions in setup times and lot sizes, or using alternate routings and operation overlapping. Doing so can improve flow time and tardiness performance in cells beyond that of a comparable job shop (Garza & Smunt, 1991, Suresh, 1992, Shafer & Charnes, 1993, Suresh & Meredith, 1994).

One reason for the apparent contradiction between industry and academia regarding the effectiveness of manufacturing cells is that while industry applications implicitly consider the impact of continuous improvement and productivity on cell performance, academic studies typically do not. Manufacturing cells have the potential to yield higher productivity than job shops (Greene & Sadowski, 1985). Bringing machines and labor physically close together and assigning production responsibilities to individual cells make a cellular shop conducive to the use of team-based production. The use of teams has ramifications for job design, delegation of responsibility, feedback, and in turn productivity (Greene & Sadowski, 1985, Huang & Houck, 1985, Huber & Hyer, 1985, Suresh & Meredith, 1985). While a common unexpected outcome from implementing cells is that using the same operators in the same cells day after day yields continuous improvement (Wemmerlov and Johnson, 1997), only recently have efforts been made to incorporate this into academic analyses of cellular manufacturing.

Two approaches have been used in the literature to model the impact of performance improvements in cellular manufacturing attributable to improvements in productivity. Suresh & Meredith (1994) considered a fixed reduction in processing times attributable to similarities in parts produced within a cell. A ten percent reduction in processing times in a cellular shop coupled with reduced setup times and lot sizes enabled the shop to outperform an otherwise comparable job shop. In addition, processing time variability was shown to be lower in the cellular shop. A second approach has been to model improvements accruing from experience. According to learning curve theory, increases in cumulative output are accompanied by reductions in unit processing time (Yelle, 1979). While the rate of reduction depends on a variety of factors such as product complexity, pre-production planning, task complexity and process technology, the underlying phenomenon is that with experience, an individual or team becomes more efficient. Manufacturing cells are particularly conducive to this phenomenon. Assigning production of an item to a cell gives operators within the cell the opportunity for repetition of associated processing tasks, allowing them to improve their proficiency (Greene & Sadowski, 1985). The frequency with which the part is produced also reduces the likelihood of interruptions in the learning process that might cause processing times to regress. Working as a team, operators can visualize and achieve goals and solve problems more effectively than if they work independently. Inter cell competition may also stimulate improvements in efficiency. The result is a production environment that is more likely to yield processing time improvements than a job shop with its more individual orientation.

Two recent studies demonstrate the significance of learning in evaluating manufacturing cells. Kannan (1996) showed that a machine constrained cellular shop with a learning rate only marginally in excess of that observed in a comparable job shop, was able to yield lower mean flow time than the job shop within a short period of time. Learning was not however able to overcome the problem of high flow time variance in the cellular shop. Eckstein & Rohleder (1998) demonstrated that in the presence of learning, a dual resource constrained cellular shop outperformed a job shop over a range of conditions, including when demand patterns were uneven. Previous studies of cellular manufacturing have consistently shown that the limited routing flexibility of a cellular shop makes it particularly unsuitable to handling uneven demand patterns. This study however demonstrated that when demand is skewed towards certain part families, rapidly decreasing processing times for some parts offset imbalances in machine utilization and bottlenecks that typically occur when demand is uneven. Operator learning also reduced labor requirements. Decreasing the number of operators increased the frequency with which operators carried out tasks, enabling operators to rapidly move down the learning curve and reduce processing times.

The results of these studies illustrate that when considering learning in comparisons of cellular and job shops, the effectiveness of a cellular shop becomes more apparent. Moreover, they highlight the importance of incorporating the labor dimension into evaluations of cellular manufacturing, and in particular, the impact of labor on continuous improvement. Several studies have examined human resource issues in cellular manufacturing. However, these have focused primarily on employee attitudes and satisfaction, job design, and the effectiveness of human resource practices (Huber & Hyer, 1985, Huber & Brown, 1991, Brown & Mitchell, 1991, Huq, 1992, Shafer et al., 1995). Other than the study by Eckstein & Rohleder, few have modeled labor constrained cellular shops to evaluate how the labor resource affects performance.

Russell et al., (1991) examined labor assignment rules in a cellular shop, showing that the timing and direction of labor reassignments can impact performance. A fully flexible workforce coupled with re-assigning operators after all jobs in a machine queue had been processed, were shown to be beneficial. Wirth et al., (1993) examined the impact of scheduling rules that reduce setup frequency. They demonstrated that while significant, labor assignment decisions were secondary to scheduling decisions, and interacted significantly with scheduling rules. Morris & Tersine (1994) compared a dual resource constrained cellular shop with a similarly constrained job shop. Similar to the results from studies of machine-only constrained shops, the job shop outperformed the cellular shop. The performance of the cellular shop was however affected by labor assignment decisions. Iyer and Askin (1999) demonstrated that the degree of cross training in a dual resource constrained manufacturing cell significantly affects flow time variance. Moreover, when operators are needed to move transfer batches, staffing levels were shown to significantly affect material flows, particularly when move times are long.

While it is important to independently assess the impacts of staffing and labor assignment decisions and repetition based operator experience, it is also important to consider how this experience affects labor assignment decisions. Differences in the frequency with which an operator carries out a task and thus the time it takes to complete the task raises the question of whether operators should be assigned based on workload or operator experience. When bottlenecks develop due to labor constraints, it is not clear whether one should address the problem by reassigning operators away from tasks with which they have experience, particularly if they are not experienced at the new task. This is particularly an issue if the operator is constrained from being subsequently reassigned away from a task with which they have limited experience. The potential for teams within cells raises important questions regarding the extent to which inter-cell labor assignments and their resulting changes in team dynamics are advisable. It is for example unclear whether it is preferable to limit the range of tasks an operator is responsible for with the goal of increasing experience, or whether flexibility in assignments is more valuable. In other words, if operators are frequently re-assigned, does this compromise their ability to move down the learning curve, and what impact does this have on shop performance. This study adds to the cellular manufacturing literature by evaluating the impact of staffing level and labor assignment decisions on the ability to exploit learning within a dual resource constrained cellular shop.

2. EXPERIMENTAL DESIGN

Three experimental factors are examined which will allow conclusions to be made about the deployment of labor resources when processing times are a function of operator experience: learning rate, staffing level, and labor transfer rule.

Learning Rate

Several models of learning have been proposed (Yelle, 1979). The most commonly observed is the log linear learning model (Wright, 1936). According to this model, the time to process the n^{th} unit of an item decreases by a fixed proportion, referred to as the progress ratio ($0 \leq$ progress ratio ≤ 1), every doubling of cumulative output. The time to process the n^{th} unit, T_n, is given by

$$T_n = T_1 n^{\log r / \log 2} \tag{1}$$

where r is the learning rate or 1 – progress ratio ($0 \leq r \leq 1$), and T_1 is the time to process the first unit. Studies suggest that when learning is attributable to organizational, technological, and labor factors, progress ratios vary from 0.16 to 0.25 (Cole, 1958). When operator learning alone is considered, this figure varies between 0.06 and 0.18 (Cochran, 1969).

In this study, each time an operator processes a job at a specific machine type, there is a reduction in job processing time. Under low learning conditions, r = 0.9, which corresponds to a

90% learning curve, and under high learning conditions, r = 0.8. A third scenario under which no learning is taking place is also considered (r = 1.0). These learning rates are consistent with evidence of learning rates in practice and with the parameters used by Eckstein and Rohleder (1998). Processing time for the n^{th} job processed at the jth machine by operator i is given by

$$T_{n,ij} = T_{1,ij} n^{\log r/\log 2} \tag{2}$$

where i, and j define the operator and machine respectively, and T_1 is the base processing time.

Staffing Level

Four levels of staffing are considered. Under the tightest staffing constraint, four operators are available to staff the shop. This corresponds to twenty five percent of machines being staffed at any time. Under the loosest constraint, the shop is fully staffed by sixteen operators. Two intermediate staffing levels corresponding to staffing levels of eight and twelve operators are also included so that the impact of staffing decisions can be more fully analyzed.

Labor Assignment

There are two dimensions to the labor assignment decision. A decision must first be made regarding *when* an operator is eligible for transfer to another machine, followed by a decision regarding which machine or to *where* the operator is assigned. Two *when* heuristics have been used in previous studies of labor transfer policies in a cellular shop. These allow operators to be transferred on completion of their current job, and when there are no remaining jobs waiting to be processed at the machine to which they are currently assigned. These rules, to be referred to as EJ and EQ respectively, have been shown to be effective both in cellular shops (Russell et al., 1991, Wirth et al., 1993) and in job shops.

Several heuristics have been evaluated with respect to the *where* decision. It should be noted that an operator may be assigned to a new machine only if another operator does not currently serve that machine. Given this assumption, two where rules that have been shown to perform well both in cellular (Russell et al., 1991) and job shop environments are to assign an operator to the machine in the shop with the longest queue (LNQ), or whose queue contains the job with the earliest due date (EDD). In a cellular shop in which learning is taking place, where to assign an operator takes on added significance. Assigning an operator from a task with which they have significant experience to a task with which they have limited experience can cause the learning process to be compromised, particularly if the operator does not have the opportunity to return to the original task for an extended period of time. On the other hand, assignments of this nature may over time allow operators to attain experience in multiple tasks. Since the underlying premise of this study is that operators working together within a cell have greater opportunities for learning than when they are re-assigned to another cell, the distinction between intra-cell assignments and inter-cell assignments is significant. To examine this, six *where* heuristics rules are considered. The LNQ and EDD rules as described above are applied without regard to cell affiliation, to machines that are not currently staffed. It should be noted that when the shop is fully staffed, no labor transfers take place. To partially constrain labor flexibility, the LNQ-P and EDD-P variants of the LNQ and EDD rules stipulate that operators can be re-assigned outside their primary cell only if there is no work remaining within their primary cell. If they are assigned away from their primary cell, they are returned there, provided there is work at an un-staffed machine, when they are next eligible for re-assignment. To further constrain labor flexibility, the LNQ-C and EDD-C rules preclude any assignment of operators away from their primary cell. Combining *when* and *where* heuristics yields a total of twelve labor transfer rules.

3. SHOP DESIGN

The shop consists of four identical flow line cells, each containing four different machines. Four part families each containing five part types, are processed within each cell. Parts require an average of 3.2 operations with no more than one at the same machine. Jobs arrive according to an exponential distribution with mean inter-arrival time established to yield mean operator utilization of eighty five percent. Given that learning occurs within the shop, mean inter-arrival time must be continually adjusted to maintain a constant labor utilization rate. This requires that the average learning rate be applied to the total number of job arrivals. An estimate of the average amount of time required to process the current job can thus be made. This estimate is then used to adjust the interarrival rate to maintain the required labor utilization rate.

Base processing time is exponentially distributed with a mean of twenty minutes. When switching between two different families, setup time is twenty percent of the base processing time. Setup time for jobs from the same family is considered to be negligible. Total operation time is given by the sum of the base processing time adjusted for learning, and setup time. Jobs are assigned a due date using the total work rule (TWK) with the control parameter set so that twenty five percent of jobs are tardy. Work content is computed based on the job processing time adjusted for estimated learning. Jobs are dispatched at each machine based on shortest total operation time (SOT), the sum of a job’s setup time and its processing time. A job belonging to a family for which a machine is currently setup will thus tend to have a higher priority than other jobs since processing the job will not require the current setup to be broken. Since the SOT rule is used to dispatch jobs at each machine, the sequence by which jobs are processed at a machine may not be the same for all machines. Jobs require one operator who is responsible for loading, processing, and unloading the job. Once assigned, the operator remains with the job until the current operation is complete. The simulation was developed using the SLAM II simulation language (Pritsker, 1987).

The replication deletion method (Law et al., 1991) was used to collect fifty independent samples of shop performance for each combination of experimental factors. For each run, the simulation was allowed to continue for a period of 10,000 simulated time units with no learning taking place to eliminate all transient effects (steady state was actually reached after 5,000 units of time). Data was then discarded and the simulation run with the required learning rate until 5,000 jobs were completed. Data was collected for three performance measures, the mean and standard deviation of flow time, and mean tardiness.

4. RESULTS

Analysis of variance was carried out of the labor assignment strategies for each combination of staffing level and learning rate. This is consistent with management being concerned about the effects of labor assignment decisions in the context of specific staffing decisions and learning conditions. Since machine utilization varies with the number of operators given the assumption of constant labor utilization, this also allows results to be presented under conditions of constant labor and machine utilization. Results indicate that except when the shop is fully staffed, all main effects are significant (Table 1, $\alpha = 0.05$). To further examine the impact of labor transfer decisions, Tukey post hoc tests were carried out at each learning rate.

Sixteen Operators

As indicated by analysis of variance, the effect of labor assignment rule is statistically insignificant for all learning rates when the shop is fully staffed.

Staffing Level	Learning Rate	Mean Flow Time		Std. Dev. Flow Time		Mean Tardiness	
		F	p	F	p	F	p
16	1.0	1.21	0.28	1.33	0.20	1.13	0.34
	0.9	0.64	0.80	0.52	0.89	0.47	0.92
	0.8	0.91	0.54	0.98	0.46	0.98	0.47
12	1.0	386.08	0.00	205.41	0.00	322.75	0.00
	0.9	865.82	0.00	238.67	0.00	497.08	0.00
	0.8	2577.48	0.00	201.10	0.00	399.32	0.00
8	1.0	1140.41	0.00	513.89	0.00	866.59	0.00
	0.9	179.07	0.00	69.49	0.00	90.88	0.00
	0.8	849.36	0.00	92.92	0.00	148.33	0.00
4	1.0	1007.62	0.00	543.18	0.00	753.77	0.00
	0.9	123.01	0.00	154.15	0.00	87.43	0.00
	0.8	500.14	0.00	173.94	0.00	233.79	0.00

Table 1. Analysis of Variance Results

Twelve Operators

In the absence of learning, when or to which machine an operator is assigned has no statistically significant impact on performance if inter cell assignments are permitted (Table 2). Performance however is consistently poorest when operators can be assigned only within their primary cell. Mean flow time and tardiness performance are compromised further when assignments are delayed until all jobs in the current queue are completed. At a learning rate of r = 0.9 however, constraining operators to remain within their primary cell consistently yields superior performance. When or to which machine an operator is assigned only impacts mean tardiness performance, a statistically significant advantage accruing from assignments on completion of the current job to the job with the earliest due date. For all performance measures, inter cell assignments can yield good performance if priority is given first to intra cell assignments and assignments take place on completion of the current job. Assignments that do not attempt to restrict operators to their primary cell to leverage learning opportunities consistently perform poorly. These results repeat themselves as learning increases further (r =

0.8). However, an important distinction is that for measures of flow time performance, assignments not subject to cell constraints and made on completion of the current job, have a significant negative impact on performance.

Learning Rate	Mean Flow Time (Minutes)		Std. Dev. Flow Time (Minutes)		Mean Tardiness (Minutes)	
r = 1.0	EJ-EDD-U	172.22	EJ-EDD-U	111.75	EJ-EDD-U	15.10
	EQ-EDD-U	172.80	EQ-LNQ-U	111.75	EQ-EDD-U	15.50
	EQ-LNQ-U	173.57	EQ-EDD-U	112.81	EQ-LNQ-U	16.05
	EJ-LNQ-U	174.07	EQ-LNQ-P	114.64	EJ-LNQ-U	16.61
	EQ-LNQ-P	174.84	EQ-EDD-P	117.30	EJ-EDD-P	16.69
	EJ-EDD-P	175.44	EJ-EDD-P	117.88	EQ-LNQ-P	17.04
	EQ-EDD-P	176.46	EJ-LNQ-U	118.22	EQ-EDD-P	17.83
	EJ-LNQ-P	177.72	EJ-LNQ-P	120.09	EJ-LNQ-P	18.17
	EJ-EDD-C	218.71	EJ-EDD-C	184.04	EJ-EDD-C	39.69
	EJ-LNQ-C	222.08	EQ-EDD-C	211.63	EJ-LNQ-C	45.47
	EQ-EDD-C	240.45	EQ-LNQ-C	219.15	EQ-EDD-C	61.58
	EQ-LNQ-C	244.95	EJ-LNQ-C	238.62	EQ-LNQ-C	65.07
r = 0.9	EJ-EDD-C	68.93	EJ-EDD-C	41.34	EJ-EDD-C	3.17
	EJ-LNQ-C	69.38	EJ-LNQ-C	42.03	EJ-LNQ-C	3.63
	EQ-EDD-C	69.85	EQ-EDD-C	42.07	EQ-EDD-C	4.03
	EQ-LNQ-C	70.02	EQ-LNQ-C	42.25	EQ-LNQ-C	4.08
	EJ-LNQ-P	81.69	EJ-LNQ-P	50.91	EJ-LNQ-P	7.25
	EJ-EDD-P	82.02	EJ-EDD-P	51.41	EJ-EDD-P	7.39
	EQ-EDD-P	86.42	EQ-LNQ-P	55.52	EQ-EDD-P	9.08
	EQ-LNQ-P	86.62	EQ-EDD-P	55.59	EQ-LNQ-P	9.08
	EQ-EDD-U	87.23	EQ-EDD-U	56.15	EJ-EDD-U	9.19
	EJ-EDD-U	87.37	EQ-LNQ-U	56.45	EQ-EDD-U	9.31
	EQ-LNQ-U	87.55	EJ-EDD-U	56.70	EQ-LNQ-U	9.52
	EJ-LNQ-U	87.70	EJ-LNQ-U	57.73	EJ-LNQ-U	9.77
r = 0.8	EJ-EDD-C	29.90	EJ-EDD-C	22.48	EJ-EDD-C	0.35
	EQ-EDD-C	30.13	EQ-EDD-C	22.67	EJ-LNQ-C	0.43
	EJ-LNQ-C	30.15	EJ-LNQ-C	22.89	EQ-EDD-C	0.47
	EQ-LNQ-C	30.29	EQ-LNQ-C	22.92	EQ-LNQ-C	0.51
	EJ-LNQ-P	53.70	EJ-LNQ-P	43.58	EJ-LNQ-P	5.30
	EJ-EDD-P	54.07	EJ-EDD-P	44.45	EJ-EDD-P	5.31
	EQ-EDD-P	62.53	EQ-LNQ-U	49.00	EQ-EDD-U	7.71
	EQ-EDD-U	62.80	EQ-EDD-U	49.39	EQ-LNQ-U	7.96
	EQ-LNQ-U	63.11	EQ-EDD-P	49.47	EQ-EDD-P	8.09
	EQ-LNQ-P	63.29	EQ-LNQ-P	50.95	EJ-EDD-U	8.21
	EJ-EDD-U	64.46	EJ-EDD-U	56.31	EQ-LNQ-P	8.64
	EJ-LNQ-U	66.09	EJ-LNQ-U	71.55	EJ-LNQ-U	10.78

Table 2. Tukey Post Hoc Analysis – Twelve Operators

Eight Operators

In the absence of learning, mean flow time is lowest when inter cell assignments are permitted without restriction (Table 3). Assignments that give priority to intra cell assignments also perform well. When or to which machine an assignment is made has no consistent impact on performance. Assignments that constrain operators to remain within their primary cell consistently yield poor performance. This is exacerbated when assignments are delayed until all work in the current queue is completed. Results for the remaining performance measures are similar with two exceptions. First, the advantages of unconstrained assignment are less pronounced. Second, when operators are constrained to their primary cell, there is no consistent advantage with respect to the standard deviation of flow time when operators are assigned on completion of the current job, as is the case for the remaining performance measures.

When r = 0.9, mean flow time is in general lowest when only intra cell assignments are permitted. If operators are assigned on completion of the current job, performance can be matched when priority is given to intra cell assignments. Performance is consistently poor when operators are assigned without regard to their primary cell. In contrast, the standard deviation of flow time is lowest when flexibility exists to assign operators outside the primary cell when no work remains there, if assignments are made on completion of the current job. Other assignment rules that give priority to intra cell assignments also perform well. Performance is in general poorest when operators must remain in their primary cell, though in one case (EJ-EDD-C), strict intra-cell assignments yield good performance. Conversely, an assignment rule that provides a high degree of assignment flexibility (EJ-LNQ-U) yields the poorest performance. Mean tardiness is affected more by when operators are assigned than to the cell to which they are assigned. It is in general lowest when operators are assigned on completion of the current job to the job with the earliest due date, regardless of the cell in which it resides. Poorest performance is obtained when there are no cell constraints and operators are assigned to the job with the longest queue. Performance is also poor when operators must remain in their primary cell and assigned on completion of all jobs in the current queue.

Learning Rate	Mean Flow Time (Minutes)		Std. Dev. Flow Time (Minutes)		Mean Tardiness (Minutes)	
r = 1.0	EJ-EDD-U	139.73	EJ-EDD-U	78.24	EJ-EDD-U	7.13
	EQ-EDD-U	141.75	EQ-EDD-U	78.24	EQ-EDD-U	8.46
	EJ-LNQ-U	144.99	EQ-LNQ-U	79.22	EJ-EDD-P	10.70
	EQ-LNQ-U	145.27	EJ-EDD-P	85.44	EQ-LNQ-U	10.84
	EJ-EDD-P	147.44	EQ-EDD-P	86.12	EJ-LNQ-U	11.75
	EQ-EDD-P	148.83	EQ-LNQ-P	87.72	EQ-EDD-P	12.91
	EQ-LNQ-P	150.65	EJ-LNQ-U	93.07	EQ-LNQ-P	14.18
	EJ-LNQ-P	153.33	EJ-LNQ-P	94.80	EJ-LNQ-P	14.87
	EJ-EDD-C	215.77	EJ-EDD-C	175.09	EJ-EDD-C	48.39
	EJ-LNQ-C	226.62	EQ-EDD-C	186.22	EJ-LNQ-C	61.85
	EQ-EDD-C	238.88	EQ-LNQ-C	190.01	EQ-EDD-C	71.83
	EQ-LNQ-C	242.53	EJ-LNQ-C	266.88	EQ-LNQ-C	75.52
r = 0.9	EJ-EDD-C	67.38	EJ-EDD-P	39.73	EJ-EDD-C	4.07
	EJ-EDD-P	71.03	EJ-LNQ-P	40.44	EJ-EDD-P	5.02
	EJ-LNQ-C	71.27	EQ-EDD-P	43.12	EJ-LNQ-P	5.82
	EQ-EDD-C	71.57	EQ-LNQ-P	43.80	EJ-EDD-U	6.20
	EJ-LNQ-P	71.64	EJ-EDD-C	45.00	EQ-EDD-P	6.84
	EQ-LNQ-C	72.44	EQ-EDD-U	45.33	EQ-LNQ-P	7.15
	EQ-EDD-P	75.35	EQ-LNQ-U	45.78	EJ-LNQ-C	7.17
	EQ-LNQ-P	75.46	EJ-EDD-U	46.28	EQ-EDD-U	7.21
	EJ-EDD-U	76.61	EQ-EDD-C	47.74	EQ-EDD-C	7.49
	EQ-EDD-U	78.26	EQ-LNQ-C	48.93	EQ-LNQ-C	8.17
	EQ-LNQ-U	78.97	EJ-LNQ-C	53.31	EQ-LNQ-U	8.40
	EJ-LNQ-U	80.40	EJ-LNQ-U	56.77	EJ-LNQ-U	9.55
r = 0.8	EJ-EDD-C	26.25	EJ-EDD-C	21.67	EJ-EDD-C	0.36
	EQ-EDD-C	27.35	EQ-EDD-C	22.21	EQ-EDD-C	0.83
	EQ-LNQ-C	27.45	EQ-LNQ-C	22.56	EJ-LNQ-C	0.87
	EJ-LNQ-C	27.54	EJ-LNQ-C	24.63	EQ-LNQ-C	0.94
	EJ-EDD-P	39.71	EJ-LNQ-P	29.08	EJ-EDD-P	2.57
	EJ-LNQ-P	39.93	EJ-EDD-P	29.22	EJ-LNQ-P	2.98
	EQ-LNQ-P	46.75	EQ-EDD-P	35.05	EQ-EDD-P	5.11
	EQ-EDD-P	46.80	EQ-LNQ-P	35.09	EQ-LNQ-P	5.28
	EQ-EDD-U	51.37	EQ-EDD-U	40.49	EQ-EDD-U	6.23
	EJ-EDD-U	52.33	EQ-LNQ-U	42.10	EJ-EDD-U	6.61
	EQ-LNQ-U	53.02	EJ-EDD-U	48.89	EQ-LNQ-U	7.93
	EJ-LNQ-U	57.96	EJ-LNQ-U	96.83	EJ-LNQ-U	13.05

Table 3. Tukey Post Hoc Analysis – Eight Operators

As learning increases further (r = 0.8), the advantages of allowing only intra cell assignments are more apparent. Both mean flow time and tardiness are lowest regardless of when or to which machine operators are assigned if they remain within their primary cell. This is followed by assignments where priority is given to intra cell assignments on completion of the current job. Performance is consistently poorest when operators are assigned without regard to their primary cell. Results for the standard deviation of flow time are similar though the impact of intra versus inter cell assignments is less pronounced. When priority is given to intra cell assignments on completion of the current job, performance is comparable to when operators are assigned only within their primary cell. Conversely, when operators are assigned on completion of all jobs in the current cell, performance is similar to when assignments are unconstrained with respect to cell.

Four Operators

Under conditions of no learning, performance is consistently best when there are no constraints on cell assignments (Table 4). This is particularly evident for mean flow time performance. Performance is best when operators are assigned to whichever machine in the shop contains the job with the earliest due date. Other assignment rules that do restrict operators to particular cells also yield good performance. Mean tardiness performance is also best when operators can be assigned without regard to cell, to the job with the earliest due date. In addition to other assignment rules that do not impose cell restrictions, one that gives priority to intra cell assignments (EJ-EDD-P) also yields good performance. The advantages of unconstrained cell assignments are less apparent with respect to the standard deviation of flow time. Several assignment rules that give priority to assignments within the primary cell perform as well as those that do not impose cell restrictions. Performance is consistently poor when

Learning Rate	Mean Flow Time (Minutes)		Std. Dev. Flow Time (Minutes)		Mean Tardiness (Minutes)	
r = 1.0	EJ-EDD-U	174.57	EJ-EDD-U	149.24	EJ-EDD-U	5.02
	EQ-EDD-U	191.80	EQ-EDD-U	150.04	EQ-EDD-U	13.20
	EJ-LNQ-U	203.40	EQ-LNQ-U	158.35	EJ-EDD-P	18.07
	EQ-LNQ-U	207.08	EJ-EDD-P	179.50	EQ-LNQ-U	26.71
	EJ-EDD-P	214.31	EQ-EDD-P	184.20	EJ-LNQ-U	30.36
	EQ-EDD-P	228.58	EQ-LNQ-P	187.67	EQ-EDD-P	35.01
	EQ-LNQ-P	234.87	EJ-LNQ-U	257.23	EQ-LNQ-P	40.14
	EJ-LNQ-P	243.16	EJ-LNQ-P	273.41	EJ-LNQ-P	43.14
	EJ-EDD-C	432.14	EJ-EDD-C	413.48	EJ-EDD-C	155.51
	EJ-LNQ-C	451.00	EQ-EDD-C	426.87	EJ-LNQ-C	189.58
	EQ-EDD-C	486.60	EQ-LNQ-C	442.60	EQ-EDD-C	213.32
	EQ-LNQ-C	512.04	EJ-LNQ-C	845.61	EQ-LNQ-C	234.95
r = 0.9	EJ-EDD-U	82.48	EJ-EDD-P	58.27	EJ-EDD-P	5.75
	EJ-EDD-P	88.40	EQ-EDD-P	63.00	EJ-LNQ-P	11.01
	EJ-LNQ-P	91.31	EQ-LNQ-P	67.65	EQ-EDD-P	12.17
	EQ-EDD-P	95.10	EJ-LNQ-P	73.35	EJ-EDD-C	13.98
	EQ-LNQ-P	99.78	EJ-EDD-C	87.67	EQ-LNQ-P	15.43
	EJ-EDD-C	113.04	EQ-EDD-C	94.29	EJ-LNQ-C	26.08
	EJ-LNQ-C	114.14	EQ-LNQ-C	99.36	EQ-EDD-C	26.76
	EQ-EDD-C	120.37	EJ-EDD-U	116.53	EQ-LNQ-C	31.80
	EQ-LNQ-C	125.79	EQ-EDD-U	121.62	EJ-EDD-U	34.53
	EJ-LNQ-U	130.92	EQ-LNQ-U	130.35	EQ-EDD-U	42.64
	EQ-EDD-U	133.69	EJ-LNQ-C	137.57	EJ-LNQ-U	45.35
	EQ-LNQ-U	144.84	EJ-LNQ-U	286.66	EQ-LNQ-U	52.29
r = 0.8	EJ-EDD-C	28.40	EJ-EDD-P	27.09	EJ-EDD-C	1.06
	EQ-EDD-C	31.04	EJ-EDD-C	28.77	EJ-EDD-P	1.89
	EJ-LNQ-C	31.86	EJ-LNQ-P	31.05	EQ-EDD-C	3.02
	EQ-LNQ-C	32.69	EQ-EDD-C	31.09	EJ-LNQ-C	3.43
	EJ-EDD-P	34.47	EQ-EDD-P	32.91	EJ-LNQ-P	3.77
	EJ-LNQ-P	36.78	EQ-LNQ-C	34.10	EQ-LNQ-C	4.23
	EQ-EDD-P	40.10	EQ-LNQ-P	34.43	EQ-EDD-P	5.08
	EQ-LNQ-P	41.33	EJ-LNQ-C	36.36	EQ-LNQ-P	5.99
	EJ-EDD-U	56.91	EQ-EDD-U	56.02	EJ-EDD-U	13.73
	EQ-EDD-U	57.30	EQ-LNQ-U	61.90	EQ-EDD-U	14.29
	EQ-LNQ-U	62.31	EJ-EDD-U	63.11	EQ-LNQ-U	19.77
	EJ-LNQ-U	64.38	EJ-LNQ-U	145.00	EJ-LNQ-U	23.65

Table 4. Tukey Post Hoc Analysis – Four Operators

operators are limited to assignments in their primary cell. When operators are so constrained, mean flow time is almost eighty percent higher than the poorest performance when inter cell assignments are permitted. The corresponding figures for the standard deviation of flow time and mean tardiness are fifty one percent and two hundred and sixty percent respectively. However, assigning operators on completion of the current job as opposed to all jobs in the current queue does have a significant positive impact on performance.

As the learning rate increases, the advantages of flexibility in assignments diminish. When r = 0.9, an assignment rule that offers the most flexibility (EJ-EDD-U) continues to perform very well. However, others that permit unconstrained cell assignments perform poorly. In contrast, rules that give priority to assignments within the primary cell perform well, while constraining operators to remain within their primary cell no longer has the adverse impact it does in the absence of learning. Results for the two remaining performance measures are similar. At r =0.8, there is no longer an advantage associated with flexible labor assignments. Mean flow time is lowest when operators are constrained to their primary cell. Conversely, performance is poorest when no restrictions are placed on cell assignments. For the remaining performance measures, while the adverse impact of unconstrained labor assignments is again apparent, the advantages of constraining operators to remain in their primary cell are not. For the standard deviation of flow time, whether operators are constrained to their primary cell or assigned outside only when no work remains in their primary cell, there is no difference in performance. Similarly, while constraining operators to their primary cell in general yields lower mean tardiness than when operators can be assigned outside, there is no statistically significant difference in performance.

5. DISCUSSION

When the shop is fully staffed, labor assignment rules have no impact on performance. With each machine staffed, the need to move operators between machines does not arise. The only potential effect is due to the specific machine within a cell to which an operator is assigned, but this too is insignificant. However, in partially staffed shops, not only does the labor assignment rule affect performance, its impact varies according to learning conditions. In the absence of learning, the shop with twelve operators reaps the rewards of flexibility in labor assignments (Figure 1). With no benefits accruing from task repetition, the primary goal of labor assignments is to respond to short-term shifts in workload patterns. This is accomplished by allowing operators to be assigned, if only temporarily, outside their primary cell. When operators must remain in their primary cell, intra cell assignments on completion of their current job as opposed to delaying them until all jobs at their current machine are completed, has a positive impact on performance. In other words, even limited flexibility has a beneficial impact on performance. In the presence of learning when there are benefits associated with task repetition, the primary motivation in labor assignments shifts from providing flexibility to achieving high processing time efficiency. Even at a low learning rate (r = 0.9), there is significant advantage associated with keeping operators within their primary cell and facilitating rapid movements down the learning curve. When inter cell assignments are permitted, efforts should first be made to keep operators within their primary cell. They should then be reassigned on completion of their current job as opposed to completion of all jobs at their current machine. This ensures that when operators are assigned outside their primary cell, the opportunity for them to return arises sooner rather than later. Unrestricted inter-cell assignments consistently yield poor performance. This becomes increasingly pronounced as the learning rate increases. The adverse effect of assignment flexibility under these conditions is illustrated by the fact that when r = 0.8, unrestricted labor assignments on completion of the current job, the most flexible labor assignment rule, yields the highest mean flow time.

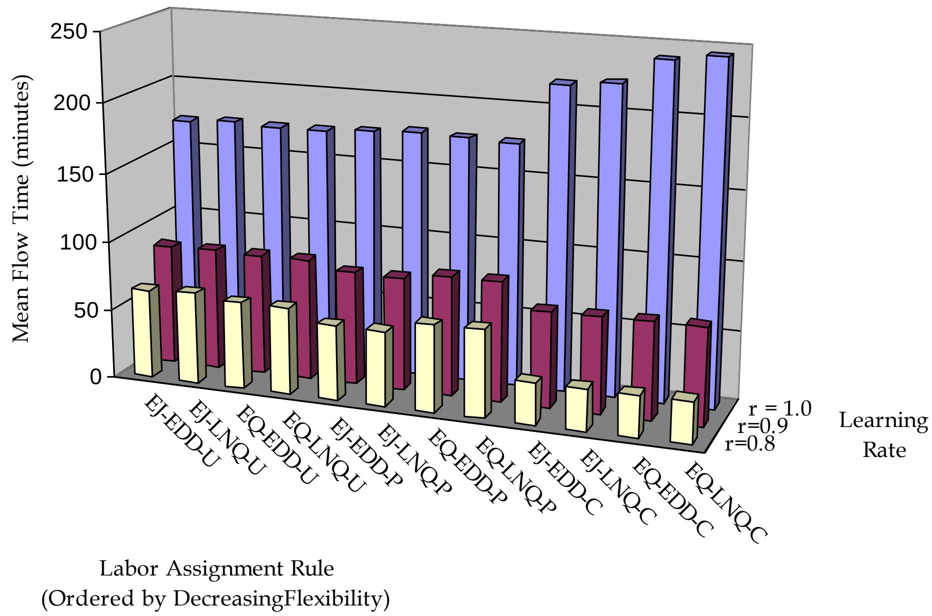

Figure 1. Sensitivity of Mean Flow Time to Labor Assignment Rule – Twelve Operators

As the shop becomes more labor constrained, the tradeoff between flexibility and efficiency comes into sharper focus. In the absence of learning, a shop with eight operators is again better served by permitting inter cell assignments (Figure 2). While mean flow time is lowest when there is unrestricted operator movement, there is no statistically significant advantage to be obtained from unrestricted movement for the remaining performance measures (Figure 3). However, it should be noted that the penalty associated with allowing only intra cell assignments is substantially larger than for the shop with twelve operators. For example, the lowest mean flow time achieved when inter cell assignments are permitted is forty one percent higher than the poorest performance when intra cell assignments are permitted. The corresponding figures for the standard deviation of flow time and mean tardiness are eighty-five and two hundred and twenty five percent respectively. In contrast, for the shop with twelve operators, the corresponding figures are only twenty-three, fifty three, and one hundred and twenty percent respectively. At a low learning rate (r = 0.9), permitting only intra cell assignments consistently yields low mean flow times. However, doing so can result in high flow time variance and thus mean tardiness. In contrast, preferring but not requiring intra cell assignments also results in relatively low mean flow times but is not as sensitive to problems associated with high flow time variance. These differences however disappear as the learning rate increases and the advantages of increased efficiency offset the disadvantages associated with limited assignment flexibility.

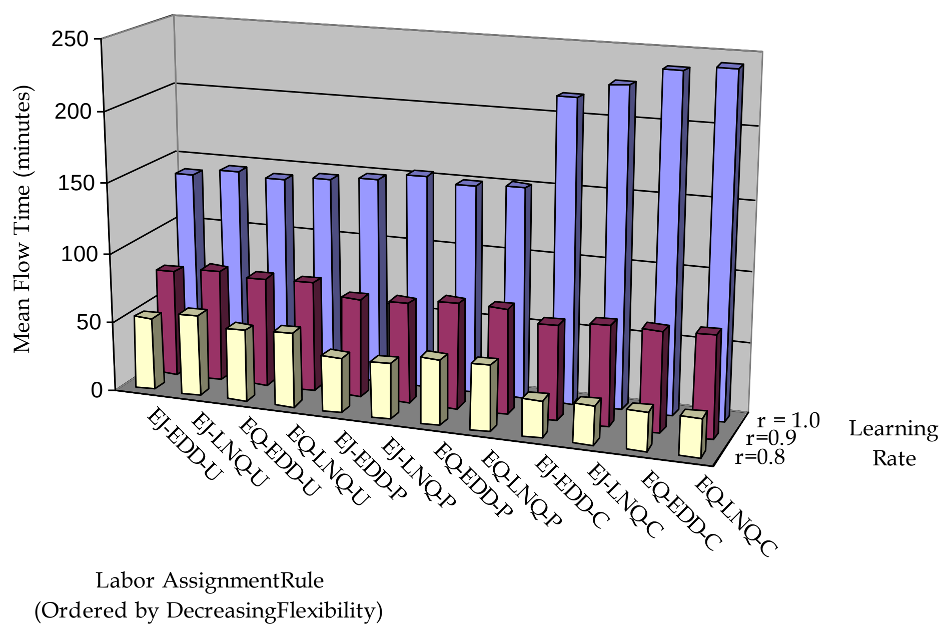

Figure 2. Sensitivity of Mean Flow Time to Labor Assignment Rule – Eight Operators

In the most tightly labor constrained shop, substantial learning is required to offset the losses in assignment flexibility attributable to permitting only intra cell assignments (Figure 4). At a learning rate of r = 0.9, restricting operators to their primary cell cannot fully offset problems caused by the tight labor constraint, indicating the need for some assignment flexibility. However, the loss in learning opportunities resulting from unrestricted labor assignments is apparent. As the learning rate increases (r=0.8), restricted labor assignments do

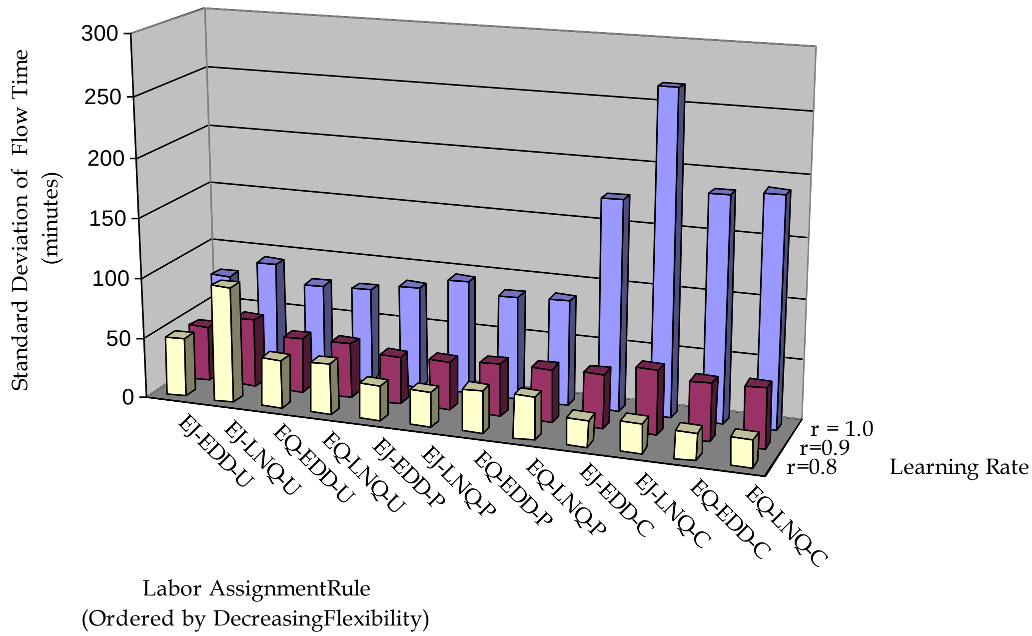

Figure 3. Sensitivity of Standard Deviation of Flow Time to Labor Assignment Rule – Eight Operators

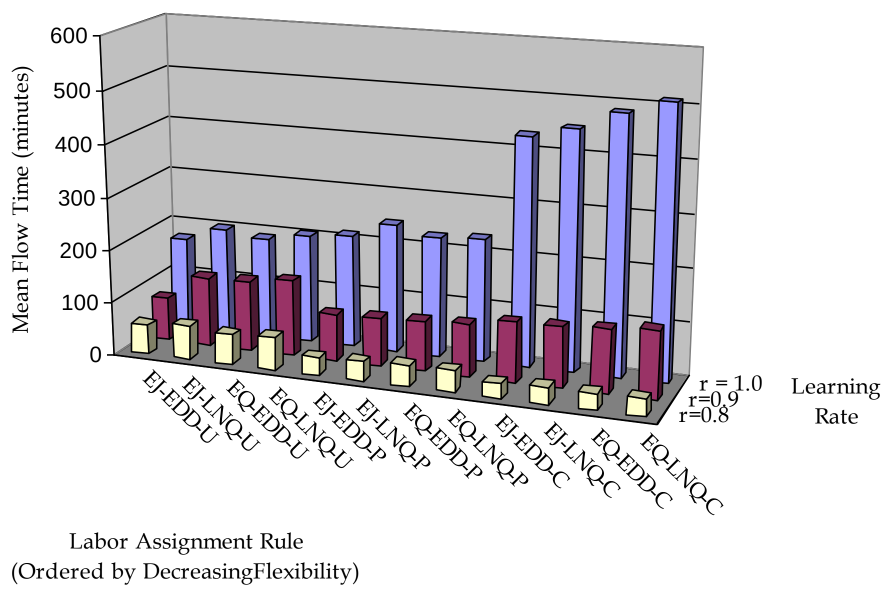

Figure 4. Sensitivity of Mean Flow Time to Labor Assignment Rule – Four Operators

not benefit flow time variance and thus mean tardiness as much as they do mean flow time (Figure 5). When operators are restricted to their primary cell, jobs in those cells are completed rapidly. However, a tight labor constraint coupled with the inability of operators to move between cells, means that short term imbalances in cell workloads can cause process time variability in heavily loaded cells to increase. This can be offset by allowing operators to respond to shifts in workload patterns by moving between cells while making every effort to leverage learning opportunities within their primary cell.

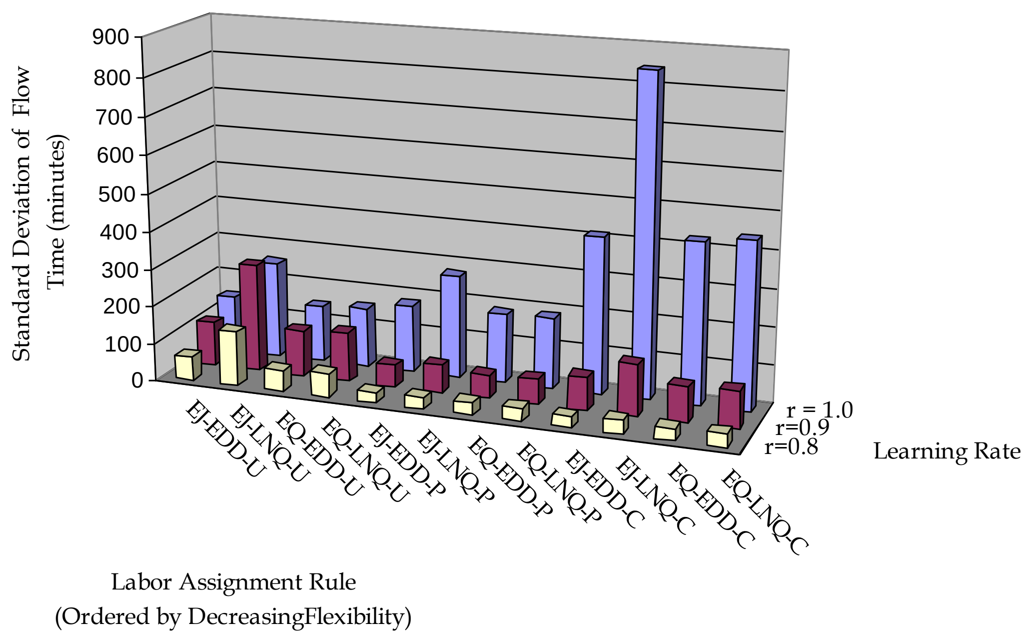

Figure 5. Sensitivity of Standard Deviation of Flow Time to Labor Assignment Rule – Four Operators

Further insight can be obtained by examining the sensitivity of cell constraints under different learning conditions. Using assignments on completion of the current job to the job with the earliest due date for illustration, it can be seen that the impact of restricting operators to their primary cell is highly sensitive to learning conditions for both mean flow time and tardiness (Figure 6). In the absence of learning, not permitting inter cell assignments significantly hampers performance, while when learning occurs, efficiencies associated with rapid process time reductions significantly aid performance. In contrast, assignment rules that

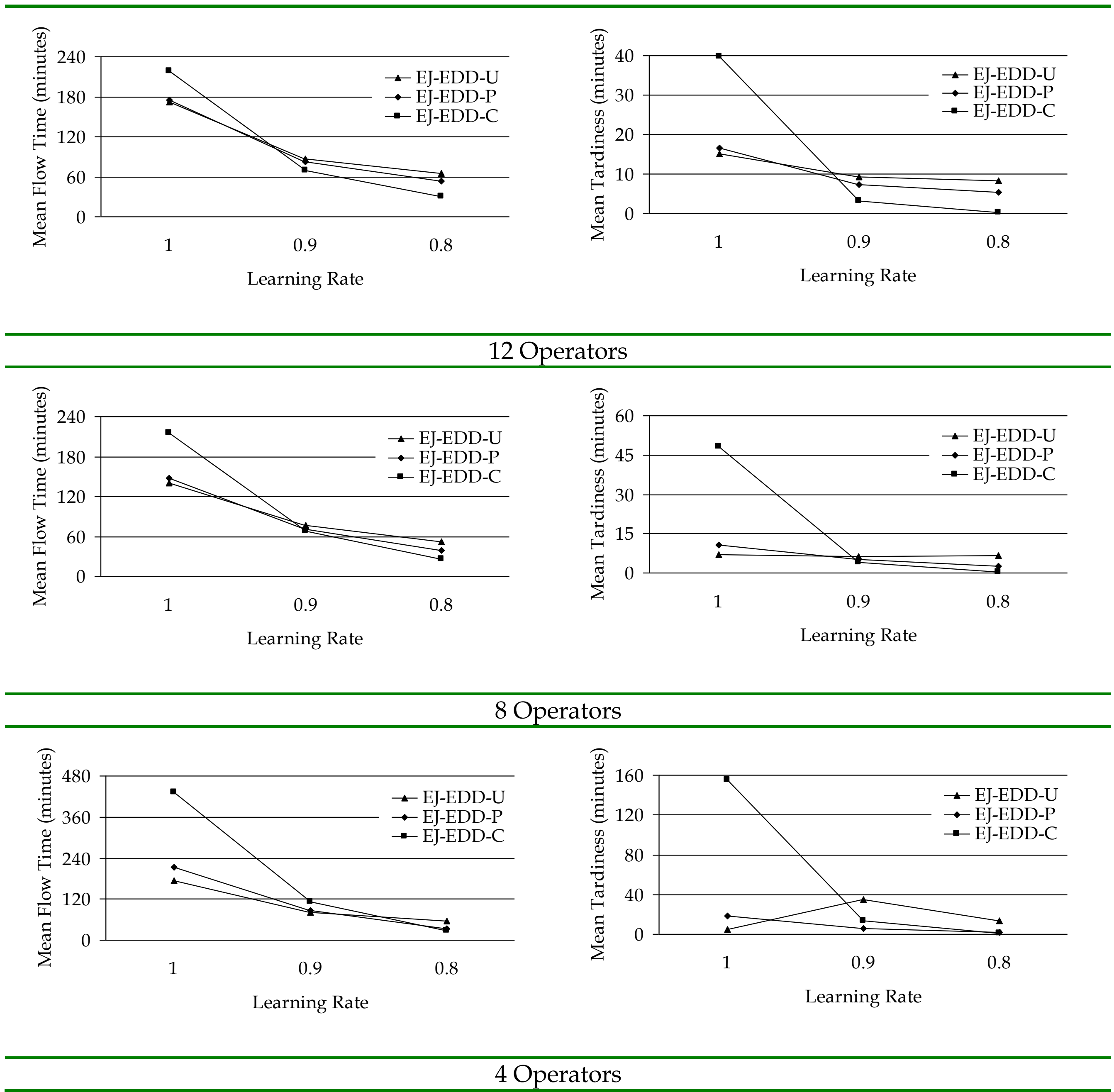

Figure 6. Sensitivity of Labor Assignment Rule to Learning Rate

permit inter cell assignments are in general less sensitive to changes in learning rate and perform more similarly to each other. As the shop becomes more tightly labor constrained (four or eight operators), allowing inter cell assignments can always be counted on to provide good if not optimal mean flow time performance. Results for mean tardiness are similar, the use of inter-cell assignments performing fairly well even with a loose labor constraint. It is of note that for the most tightly labor constrained shop with unconstrained inter cell assignments mean tardiness increases as learning is first introduced but subsequently falls. Partial rather than complete assignment flexibility is thus needed under these conditions to be assured of always yielding favorable performance.

6. CONCLUSIONS

Manufacturing cells are typically labor constrained yet little research has examined how labor resources impact their operation. The results of this study illustrate the impact that assignment decisions have on manufacturing cells, both under different learning conditions and for different staffing levels. The results demonstrate that merely including the labor resource in studies of manufacturing cells is insufficient and that failure to consider the dynamics of operator performance can seriously hinder performance. The relative performance of labor assignment rules is not only sensitive to the rate at which operators learn it is also highly sensitive to labor constraints due to the tradeoff between operating efficiency and the need for flexibility in operator deployment. Given management decisions about staffing levels, appropriate decisions must be made to allow a shop to reach the right balance between responsiveness to changing workload patterns, and developing operator experience. Understanding the tradeoff between assignment flexibility and processing efficiency can permit a shop to more effectively use its labor resources. Conversely, failure to do so can result in lost opportunities to learn, and a shop, which, while in principle able to deal effectively with repetitive processing, failing to do so.

The results suggest several possible areas for future study. This study assumed that operators were homogeneous in their abilities and propensities to learn. The ability of operators to exploit learning opportunities however depends on their having the appropriate capabilities and aptitudes as well as opportunities to develop them. Constrained training resources, targeted correctly, may thus be as effective or more so, than a larger, poorly targeted training program. Learning loss or interruptions to the learning process is another area for future study. Learning loss can occur if a significant period of time elapses between successive repetitions of a task by an operator. Learning loss may affect the desirability of inter-cell labor transfers, particularly in a severely labor constrained shop in which operators are unable to return to their primary cell.

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