EFFECTIVENESS OF CELLULAR MANUFACTURING

Previous studies suggest that despite their intuitive appeal, cellular manufacturing systems are only effective in a batch production environment under a limited set of conditions. However, these studies have not taken into account the potential for productivity improvements unique to shops organized around product and work groups. Improvements that yield processing time reductions and rapid movement down the learning curve may offset the limited flexibility that typically compromises the performance of cellular shops. This paper demonstrates that if a cellular shop can yield even–marginally greater reductions in processing times than a job shop, it can outperform a job shop under conditions previously thought to be unfavorable to a cellular shop. Learning curve theory is used to show that this can be achieved at modest levels of output and also under conditions not typically associated with cellular shop configurations.

Keywords : Cellular Manufacturing, Group Technology, Simulation, Learning Curve

1. Introduction

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Cellular manufacturing (CM) has attracted considerable attention from both practitioners and academics as ways are sought to improve production efficiency and lead times in a batch manufacturing environment. Although organizing production around part families to exploit processing similarities has intuitive appeal, questions exist regarding its effectiveness. Cellular systems appear to perform well relative to comparable job shops only under a limited set of conditions (Flynn & Jacobs, 1987, Morris & Tersine, 1990, Suresh, 1992), in particular when set up and material handling times are high relative to processing times, and when demand patterns are stable. If cells can be operated with lower setup times and lot sizes (Suresh, 1992) or with operations overlapping (Shafer & Charnes, 1993), similar results can be obtained. Cellular layouts are still however severely limited in their ability to respond to changes in demand patterns and in particular to workload imbalances between cells. This can be attributed to the permanent dedication of equipment to part families (Flynn & Jacobs, 1986) or loss of pooling synergy (Suresh & Meredith, 1994) which more than offsets the setup, material handling, and production control efficiencies associated with cells. To date, conclusions regarding the performance of CM systems have been based primarily on studies of technical aspects of system design. Numerous simulation and analytic studies of cell formation approaches, layout and its impact on material handling and production control, and setup reduction, have been carried out. In contrast, little attempt has been made to quantify the contribution of less technical aspects of process design to system performance. Socio-technical systems theory suggests the need for a complementary fit between technical and non-technical aspects of CM system design in order to achieve optimal system performance (Huber & Brown, 1991). However, the literature lacks significant discussion of the relationship of, for example, job and process design, to productivity and performance in cellular shops.

The unique physical characteristics of cellular layouts offer potential for improvements in productivity that previous studies have under emphasized. This study examines the implications of productivity improvements and learning for CM systems. A cellular shop that yields processing efficiencies attributable to its unique design characteristics is compared to an otherwise comparable job shop, to demonstrate whether such processing efficiencies can overcome the apparent limitations of cellular systems.

2. Past Literature

2.1 Cellular Manufacturing & Job/Process Design

Several studies have suggested that benefits can be derived from a CM system due to the opportunities for job/process design that its physical orientation presents. Giving operators wide ranging responsibilities for a family of parts as opposed to a single operation, may increase job satisfaction (Fazakerley, 1973, 197 6, Greene & Sadowski, 1984, Huang& Houck, 1985). The identification with a finished product that results, may in turn increase productivity. Since operators see the entire production process rather than individual processes, they are in a better position to set goals and manage the production process (Greene & Sadowski, 1984, Huber & Hyer, 1985). Organization of the work force in teams and with all equipment in close proximity, can improve visibility and feedback. This can be used to promote opportunities for group process improvement activities and problem solving (Huang & Houck, 1985, Huber & Hyer,1985) which in turn can positively affect quality. Cells offer greater opportunities for cross training which increases labor flexibility. The use of cells promotes a part family orientation within the workforce that job shops typically cannot replicate, which again has implications for quality and performance (Suresh & Meredith, 1985). Although claims have been made regarding the relationships between job and process design and the performance of CM systems, few experimental studies have been carried out to evaluate them. Those that have primarily examined human resource issues such as job satisfaction, training, and employee attitudes. Results suggest that cell operators may face problems not encountered in functional layouts (Brown & Mitchell, 1991), for example inadequate training to prepare them for the increased scope of their jobs and reliance on each other. Other aspects of converting from afunctional to a cellular layout may also pose difficulties, for example changes in technology. Huber & Hyer (1985) suggested that operator performance as measured by evaluations by supervisors is higher in cellular shops than in job shops. No research however has examined the impact of job process design on traditional measures of shop performance such as flow time and due date performance.

2.2 Cellular Manufacturing & Learning

One implication of a CM system suggested by the discussion on process design is the greater potential it offers than a job shop for reductions in processing times associated with increases in output. Learning curve theory suggests that the rate at which processing time reductions occur is affected by a large number of factors. These are surveyed in Yelle (1979). Among these factors are product complexity and pre-production planning (Wyer, 1953), and degree of labor intensity of the process (Hirsch, 1956). A cellular configuration is uniquely suited to bringing about processing efficiencies associated with increased volume. Repetitive processing of a finite set of parts by group members can increase the competence of the workforce (Greene & Sadowski, 1984). Broader involvement of operators as described earlier, can increase the scope for them to design and implement tasks with a global approach as opposed to the traditional piecemeal approach. Seeing the entire process may also allow operators to recognize the need to modify tasks more readily as conditions dictate. The rapid feedback that cells can facilitate also provides a vehicle for quality improvement. This can result in reductions in defect rates, rework, and waste, and increased consistency. All of these contribute to increasing productivity which translates to lower flow times, better due date performance, and lower levels of work in process inventory. To date, the impact of learning has been largely overlooked in studies of CM systems. Suresh & Meredith (1994) showed that reducing processing times in a cellular shop can enable it to elicit better performance than a comparable job shop. They however made the assumption that this reduction is attributable to the similarity of parts being produced within cells. Although part similarity is one reason why processing efficiencies can potentially be obtained in a cellular shop, it is not the only one. Further, one cannot discount the potential for processing efficiencies in a job shop. If a cellular configuration, by virtue of its job and process design characteristics, can elicit greater rates of learning than a job shop, this suggests an alternative route to achieve reductions in processing times within cells without precluding similar reductions in the job shop. By building and supporting an appropriate infrastructure, management has the potential to reduce processing times at a faster rate than it can in a job shop in which there is greater separation of tasks and individuals and a narrower individual view of the production process. This allows the organization to take advantage of the processing efficiencies of cellular shops without lead times, utilization, and inventory levels being compromised by limited shop flexibility. Not only does this give the organization a competitive edge in delivery and cost performance, but it increases potential market share, further increasing opportunities to move down the learning curve. Using a simulation model, this study illustrates the impact of learning, as measured by reductions in processing times, in job and cellular shops, and addresses three specific questions. Can increased learning enable a cellular shop to perform at a comparable or higher level than a job shop under conditions currently believed to be disadvantageous to a cellular shop. If so, what magnitude of increased learning is required to achieve this, and can this be realized given the required output levels. Not only will this help to explain why industry continues to claim that CM is a viable alternative to a job shop but it will allow managers to better estimate the benefits of a cellular layout.

3. Research Method

3.1 Shop Environment

Two shop environments are examined, a cellular shop and a job shop. The cellular shop is configured as three identical job shop cells similar in configuration to those in Mahmoodi et al., (1990). Each cell contains five machines of different types with no machine duplication. Twelve parts are processed within each cell. Parts require four or five operations with no more than one operation on a given machine. Cells are distinguished by the part family for which they are setup, yielding a total of thirty six parts. The job shop consists of five process departments each containing three identical machines. Parts can be processed on any machine within the corresponding department. Orders arrive according to a possession process with the mean interarrival rate established to achieve average utilization of 75% in the job shop. Orders are for a single batch of one part. All parts have the same demand probability creating a balanced part mix consistent with the capacities of each cell. Base processing time is 60 minutes per batch per operation. Batches are dispatched using the repetitive lots logic (Jacobs & Bragg, 1988) that requires batches using the current machine setup be given priority. Once no such batches remain, the next batch to be processed is selected on a first come first served basis. Given that cellular shops can perform well compared to job shops under certain conditions in the absence of learning (e.g., Morris & Tersine, 1990), this study examines their performance under conditions when they do not perform as well as anticipated. Remaining shop parameters were thus established to reduce or eliminate the inherent advantages of cellular shops. Major (inter family) setup time is normally distributed with a mean of twenty minutes and a standard deviation of five minutes (Mahmoodi, et al., 1992) yielding a base setup time processing time ratio of 1/3. This is relatively low based on past simulation and empirical evidence (e.g. Wemmerlov & Hyer, 1989, Mahmoodi et al., 1992). Minor (intra family) setup time is one quarter of the major setup time (Flynn & Jacobs, 1987). Since cells are dedicated to specific families, major setups do not occur in the cellular shop. Material handling time is equal to zero for both shops. This eliminates the material handling advantages of cellular shops that result from their linear flow patterns and close proximity of machines.

3.2 Experimental Factors

Three experiments were carried out to investigate the impact of increased learning in the cellular shop. Learning is modeled using a log-linear function (Wright, 1936) with processing times for each operation of a part decreasing at a fixed rate whenever cumulative production doubles. Although this is not the only function observed in practice, it is the most widely used (Yelle, 1979), and provides a vehicle for understanding the impact of learning. In the first experiment, denoted JS-100, the base learning rate, defined to be the learning rate in the job shop, is 100%. In other words, there is no learning effect present in the job shop. However, the cellular shop is observed under similar conditions and also when processing times follow 97.5% and 95% learning curves. Incremental learning (IL) in the cellular shop is thus established at levels of 0%, 2.5% and 5% respectively. The experiment was repeated for the same levels of incremental learning but when processing times in the job shop followed 90% (JS-90) and 80% (JS-80)learning curves. Several studies have been carried out to estimate typical learning rates in manufacturing activities. These suggest that learning rates typically range from 75 to 90 percent (e.g., Hirsch, 1956). The reader is referred to Yelle (1979) for a comprehensive review of factors affecting learning rates. The impact of these base learning rates on operation times is illustrated in Figure 1. In each case where a learning effect was present, utilization levels were maintained by increasing the interarrival rate, thereby compensating for the lower processing times.

To examine the impact of bottlenecks in the cellular configuration when demand patterns are not consistent with cell capacity, each of the above experiments was repeated under unbalanced part mix conditions. Under these conditions, two families each account for 40% of total demand. This distribution of demand is similar to that used in Wemmerlov (1993). Demand is evenly distributed within families. After initialization and batch size considerations were met, thirty replications of each of the twenty four (3 * 4 * 2) treatments were carried out. For each replication, the mean and standard deviation of flow time were recorded for different numbers of jobs completed (N) in increments of 100 for N ≤ 800. To reduce variance but maintain independence between treatments, common random numbers were used for all but one random number stream (Mihram,1974). The simulation was written in SIMAN (Pegden, 1987) and FORTRAN.

4. Results

Treatment means are presented in Tables 1 and 2. Graphs showing the relationship of mean flow time to the number of jobs completed are shown in Figures 2-5. In addition, the impact of learning on the standard deviation of flow time is shown in

Figure 6.4.1*

Mean Flow Time *

4.1.1 JS-100

When processing times are not affected by learning in either shop, mean flow time, as expected, remains unchanged as output increases. It is predictably higher in the cellular shop. Under balanced part mix conditions, the cellular shop operating at IL = 2.5%, yields performance that is poorer than that of the job shop for low output levels (Figure 2). However, for N = 800, mean flow time in the cellular shop has fallen to the extent that it is almost identical to that yielded by the job shop. Two key multiple comparisons of treatment means (Table 3) indicate that mean flow time is significantly higher for the cellular shop for N ≤ 500, but not for N = 600. Extrapolating from the curves, one can anticipate that the cellular shop may outperform the job shop as N increases further. The impact of IL = 5% is even more noteworthy. Within completion of 200 jobs, performance of the cellular shop is statistically similar to that of the job shop. The cellular shop performs significantly better than the job shop for N ≥ 400. Even when part mix is unbalanced benefits of a cellular layout are apparent (Figure 3). Although as expected it yields poorer flow time performance than the job shop, the potential exists for it to yield comparable performance when IL = 5%.

4.1.2 JS-90*

When IL = 0%, both shops as expected demonstrate decreases in mean flow time as output increases, with the job shop outperforming the cellular shop. The rate of decrease is however, greater for the cellular shop. Results suggest that underbalanced part mix conditions, the cellular layout may be able to outperform the job shop with further increases in output without incremental learning (Table 1). When the cellular shop operates at IL = 2.5%, it yields poorer flow time performance than the job shop for $N \leq 300$ (Table 3), but for $N \geq 500$, it yields significantly better performance. For IL = 5%, this crossover occurs sooner.

For N = 100, the job shop still performs significantly better. After completion of 200 jobs there is no difference in performance, but for $N \geq 300$, the cellular shop outperforms the job shop. When part mix is unbalanced, the cellular layout operating at IL = 5% yields mean flow time that is statistically comparable to that obtained in the job shop within completion of 800 jobs (Table 3). At lower levels of IL however, it appears that mean flow time may plateau at a higher level than in the job shop. (Reference: 4.1.3 JS-80)*

When processing times in both the job and cellular shops follow an 80% learning curve and part mix is balanced, there is clear evidence that the cellular shop can perform comparably to the job shop even without learning at a greater rate (Figure 4). When IL = 0%, mean flow time for the job shop is significantly lower than that of the cellular shop for $N < 700$. However, for N = 700, there is no statistically significant difference in flow time performance (Table 3). The rate of decrease in mean flow time is again greater for the cellular shop, suggesting that it may outperform the job shop as N increases further. When IL = 2.5%, the cellular shop outperforms the job shop within completion of 400 jobs. For IL = 5%, this outcome is reached within completion of 300 jobs. When part mix is unbalanced, the cellular layout is again able to yield better performance than the job shop (Figure 5). For IL = 5%, the cellular shop performs comparably to the job shop when total output is 500 jobs, and outperforms the job shop when $N \geq 800$. For lower values of incremental learning (IL = 2.5%), larger volumes are required before the cellular layout yields lower mean flow time, but as the graph shows, this should occur at output levels little higher than N = 800.

4.2 Standard Deviation of Flow Time (□%□ FT)

** Library Note: It is uncertain what "□%□ FT" was intended to represent, so it has been left as is. It is likely the standard deviation or related error, and the original sigma character wasn't read in this version.

The positive impact of learning on variance reduction in the cellular shop is also apparent, but it is not as significant as it is for mean flow time. Under all scenarios examined, the effects of learning, as expected, help to reduce the value of □%□ FT. The relationship is most clearly seen in Experiment JS-80 when part mix is unbalanced (Figure 6), though the relationship between incremental learning and □%□ FT largely repeats itself for other base learning rates and when part mix–is balanced. What differentiates the scenarios is the rate of decline in □%□ FT. This typically is greater for larger base learning rates (smaller coefficients of the learning curve), rates of incremental learning, and when part mix is unbalanced. It is important to recognize however that in each case, □%□ FT appears to level out at a significantly higher value than that for the job shop, suggesting that unless the extent of incremental learning in the cellular shop is significantly increased, flowtime variance will remain a problem.

5. Discussion

The results suggest that the effectiveness of cellular manufacturing can be increased significantly if the potential to promote processing efficiencies and exploit learning curve principles inherent in their design, is recognized. Underbalanced part mix conditions with workload evenly distributed between cells, even small amounts of incremental learning (IL = 2.5%) in the cellular shop can reduce or eliminate the adverse effects on mean flow time of the limited routing flexibility of a cellular layout. The results from experiment JS-100 suggest that only six hundred jobs need to be completed in order to eliminate differences in mean flow time performance between the cellular and job shops. This translates to the completion of on average less than twenty batches of any individual part. A wider product range would likely require higher total output before these gains are realized, but it appears that this will still not amount to unrealistic levels of demand for individual parts. Even in a dynamic part mix environment, it is not unreasonable to expect these levels of output for a part prior to it being modified or discontinued. As the base learning rate and incremental learning rate increase, so do the apparent advantages of cellular layouts. Even when part mix is unbalanced, the potential exists for processing time reductions to offset the inability of a cellular layout to distribute work effectively.

Although the observations made are not directly generalizable to shops with different operating parameters, it is not unreasonable to expect that a cellular shop will at some level of output perform at a comparable or superior level to a job shop under similar conditions if processing efficiencies inherent in its design are exploited. It is important to note that these experiments were carried out under conditions not typically conducive to cellular configurations. This serves to emphasize the effectiveness of processing time reduction in the cellular shop similar to the results of Suresh &Meredith (1994). Results also suggest that as long as there is some learning taking place, a cellular shop does not have to learn at a faster rate than a job shop in order to achieve lower flow times. Experiments JS-90 and in particular JS-80 show how mean flow times in the cellular shop decline at a faster rate than in a job shop. A major problem of cellular layouts is the queues that build at certain machines when cell workload does not match cell capacity. Reducing processing times in this environment therefore has a greater impact on queues than in the job shop where there is greater flexibility to allocate work between machines. As the learning rate in the cellular shop increases, the ability of the shop to elicit these benefits also increases. This can be seen by comparing the number of completed jobs required in order for the cellular shop to yield comparable flow times to the job shop when IL = 0%. One can surmise that when comparable learning takes place in the two shops but at a lower rate than in experiments two (JSN 90) or three JSN 80 (for example a base learning rate of 95%), a similar result will be found but at a higher level of total output. The observation that even with high faster levels of learning the cellular shop performs poorly with respect to □%□ FT is significant. Large flow time variance is typically a significant factor in poor due date performance. This again highlights the fundamental limitation of cellular layouts that their limited routing flexibility renders them unable to efficiently redistribute work in response to bottle necks. Consequently, high work in process inventories, long queues, and delays in the completion of some jobs result. Increased investment in equipment can resolve this problem, but not only may this not be feasible, this may increase problems of imbalances in utilization. Unless the issue of flexibility is also addressed, gains from reduced flow times may be eroded by the inability to efficiently meet due dates.

6. Conclusions & Future Research

By understanding the potential of learning effects, management has the means to increase the efficiency and productivity of CM systems. Results suggest that substantial benefits can be reaped from installing and maintaining an infrastructure that harnesses the unique opportunities for processing efficiencies in a cellular layout. Given the closeness of personnel, increased visibility, and team orientation discussed earlier, cells offer an ideal environment for improving feedback, process design and quality. However it is not clear whether in practice these benefits are fully realized and translated into lower processing times (Huber & Hyer, 1985). As suggested by Abernathy and Wayne (1974), learning is a process that must be understood and carefully managed if its potential is to be realized. The results also help to explain the apparent discrepancy between academic and industry evaluations of cellular manufacturing. While other academic studies have shown that production control mechanisms can help reduce the impact of inherent inflexibility of cellular shops, they have also shown that significant changes may be needed in the way the shop is operated, in order to achieve this outcome, and then only under certain circumstances. It is apparent from the results presented here that the same outcome may be a natural consequence of a cellular configuration if appropriate emphasis is placed on how work is organized and carried out. This may explain why some users of cellular systems report positive results from their use.

A number of extensions for future research are suggested by the results of the current study. This study modeled learning as a function of an operation without taking into account differences in abilities and experience of operators. With differences likely to exist in individual abilities and rates of learning, the impact of specific operators is potentially significant. Further, the time that elapses between an operator repeating operations may affect learning loss and the ability to realize a particular learning rate. These issues become more important in a labor constrained shop in which operators must each operate multiple machines, thereby increasing the time intervals described above. Differences in the learning rates of individual operators may also affect decisions regarding whether to move operators between cells, and if so, what labor allocation strategies to use. This in turn raises the issue of labor flexibility and cross training. Greater cross training may result in increased training costs, but the return may come in the form of increased operator learning and improved performance.

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