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A Comparison of Cross Training Policies in Different Job Shops

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Abstract

This research compares a set of cross-training policies represented by different numbers of cross-trained workers, additional skills per cross-trained worker, and additional machines. The policies are evaluated in job shops, represented by different efficiency losses, labour utilization, variability in processing times, and worker absenteeism. Our results show that adding one machine in each department and cross-training one or two workers from each department with one additional skill is generally sufficient to realize most of the benefits of cross-training. Cross-training is thus beneficial in most job shops, unless the cost of the minimal training and spare machines is high. Our results also show that the value of cross-training and adding machines depends very much on the environment, and it is better to spread cross-training over more workers than to train a few workers with more skills.

Keywords: Cross-training, Job shops, Computer simulation

1. Introduction

A Dual Resource Constrained (DRC) job shop is a system whereby both workers and machines are limited in capacity and are potential constraints on the system output and performance. The DRC job shop also typically has more machines than workers, with the machines and workers of the same skill grouped into the same department. Cross-training workers across different departments thus offers the flexibility to deploy workers to changing workloads, and thereby produces a better delivery and inventory performance.

Table 1 lists some of the recent studies on DRC job shops. While most of the studies reviewed by Treleven (1989) have assumed environments with homogeneous workers, recent studies have increasingly assumed environments with heterogeneous workers, i.e. workers whose efficiency varies when they work in different departments. In addition, most of the studies have focused primarily on the operational issues, such as due-date assignment, job dispatching, and worker assignment.

Previous studies cited by Treleven (1989) and more recent studies by Bobrowski and Park (1993), Malhotra and Kher (1994), Kher (2000), and Kher and Malhotra (2000) have addressed most of the issues on choosing the ‘right’ operating rules in DRC job shops. Malhotra and Kher (1994), for example, showed that allowing the transfer of a worker whenever he completes a job works best when the transfer delay is insignificant while transferring a worker only when his current job queue is empty is preferred when the transfer delay is significant.

Table 1. Classification of some recent works on DRC job shops.

	Heterogeneous workers	**Homogeneous workers**
Operational issues	Bobrowski and Park (1993)	See review by Treleven (1989)
	Malhotra and Kher (1994)	
	Kher (2000)	
	Kher and Malhotra (2000)	
Design issues	Brusco and Johns (1998)	Slomp and Molleman (2002)
	Felan and Fry (2001)	Bokhorst *et al*. (2004)

While Treleven (1989) had suggested that 'where' rules are not important in DRC job shops with homogeneous workers, Malhotra and Kher (1994) showed that 'where' rules do perform differently in job shops with heterogeneous workers. Their finding is consistent with the finding of Bobrowski and Park (1993). In DRC job shops with heterogeneous workers, both studies showed that the 'where' rule of assigning workers to their most proficient departments dominates the other 'where' rules and also reduces the importance of choosing the right 'when' and job dispatching rules.

Most previous studies, however, have ignored the design issues and examined only a single cross-training policy where all workers are trained in the same number of departments. In total, we found four studies on different cross-training policies for DRC job shops. Brusco and Johns (1998), for example, compared 36 different cross-training policies, each representing one or two additional skills per worker, 100% or 50% proficiency in the additional skills, and symmetric versus asymmetric cross-training pattern. Minimizing the staffing costs, they found that asymmetric cross-training patterns, which chain workers' skills across departments, perform best. However, as the number of additional skills increases, the value of chaining becomes less important.

In job shops with heterogeneous workers, Felan and Fry (2001) are the first to abandon the assumption of cross-training all workers in the same number of departments. They found that 'it is better to have a mix of workers with no flexibility and some workers with very high flexibility rather than all workers with equal flexibility', i.e. an unequal number of skills per worker is better than equal number of skills per worker in job shops with heterogeneous workers. In contrast, Slomp and Molleman (2002) and Bokhorst *et al*. (2004) found that equal number of skills per worker is better in environments with homogeneous workers.

Slomp and Molleman (2002) compared four rules to distribute workers' skills to work in different departments. The four rules are Critical Task, Worker Flexibility, Random, and Bottleneck Redundancy. They found that the Worker Flexibility rule, which attempts to equalize the number of skills across all workers, performs well. Bokhorst *et al*. (2004) also compared eight alternative cross-training policies, each representing either equal or unequal number of skills per worker, equal or unequal machine coverage, and maximum or minimum collective responsibility among workers to share workloads across departments. In a job shop with homogeneous workers, they found that an equal number of skills per worker, equal machine coverage, and minimum collective responsibility (especially for workers assigned to bottlenecks) produce the best mean flow time.

This research is an attempt to address the choice between equal and unequal number of skills per worker. While Felan and Fry (2001) have suggested that unequal number of skills per worker is better in environments with heterogeneous workers, Slomp and Molleman (2002) and Bokhorst *et al*. (2004) have suggested otherwise in environments with homogeneous workers. The choice between equal and unequal number of skills per worker thus remains unsolved in a broader range of environments.

This research compares a set of cross-training policies using computer simulation. The results provide useful insights on choosing the 'right' number of cross-trained workers, additional skills per cross-trained worker, and additional machines to realize the benefits of cross-training. To further provide insights on choosing the right cross-training policies in different environments, the cross-training policies are compared in a wide range of environments represented by different efficiency losses, labour utilization, variability in processing times, and worker absenteeism.

In the next few sections, we first present a simulation model of a job shop, and discuss the experimental factors and performance measures used in the study. The results are then analysed and discussed. Finally, the managerial insights are summarized in the conclusions.

2. Simulation model

A job shop with 24 workers and six departments was built using SLAM (Pritsker 1986). In the base case, cross-training is not practised, and each department has four identical machines and four workers permanently assigned to it. The job shop was built in a manner similar to those used by past studies cited by Treleven (1989) and by Bobrowski and Park (1993). For example, the number of new jobs per day is generated using a Poisson distribution. The routing, processing times, and due date of each job are then generated before the jobs are released on to the shop floor.

The routing of each job is generated such that each job can visit a department only once and with equal probability. Hence, for the first operation, a job is routed to any department with equal probability. For each subsequent operation, the same job is routed only to the unvisited departments including an exit with equal probability. This procedure produces routings with an average of 3.5 departments per job.

The processing time of each operation is generated using a Gamma distribution with a coefficient of variation of 0.5. The processing time is then truncated at 10 min and 16 h, as proposed by Davis and Mabert (2000), to eliminate any excessively short or long processing time. Most studies on DRC job shops have also assumed a mean labour utilization of 90% when cross-training is not practised (Treleven 1989). We thus set the mean number of new jobs per day at 24 and the mean processing time such that the mean labour utilization is 90% when cross-training is not practised.

On arrival, each job is assigned a due date using the Total Work Content due date rule by adding to its arrival time a processing allowance equal to a constant multiple of its total processing time. This due date rule has been cited to perform well in many DRC job shops (Treleven 1989) and is used in our model. To compare the benefit of cross-training across different environments, the due date tightness is adjusted such that 20% of the jobs are tardy in all environments when cross-training is not practised. This level of due date tightness is chosen based on a review of past values used in the literature.

Upon arrival at a department, each job is started immediately if the appropriate worker and machine are available. Otherwise, the job joins a queue. In each department, all jobs are queued from the earliest-tolatest due dates. In other words, waiting jobs within each department are processed according to the Earliest Due Date job dispatching rule. This job-dispatching rule has performed well in DRC job shops (Treleven 1989).

There are two types of workers when cross-training is practised. They are the cross-trained workers, who can work in more than one department, and the primary workers, who can work in only one department. A cross-trained worker is, thus, a more valuable resource since the worker can work in different departments. We, therefore, propose a worker assignment rule that conserves the flexible workers by assigning cross-trained workers to a department only when all its primary workers are busy. This rule thus gives the cross-trained workers the first claim to any idle time and avoids overloading them continually with jobs from different departments, providing a more equal distribution of work between the primary and cross-trained workers.

Whenever a primary worker finishes a job, he is assigned immediately to the next waiting job in his department. A primary worker thus becomes idle only when there are no waiting jobs in his department. When this happens, the idle worker joins a list of idle primary workers within his own department. The first worker in this list will then work on the next job that arrives in the department.

A cross-trained worker is able to work in different departments. Past research has shown that the ‘where’ rule of assigning cross-trained workers to their most efficient departments performs better than other ‘where’ rules, and also reduces the impact of when to transfer workers and the effect of transfer delays (Bobrowski and Park 1993, Malhotra and Kher 1994). By using the ‘where’ rule of assigning workers to their most proficient departments in our model, we thus adopt a single ‘when’ rule and argue that this combination of ‘when’ and ‘where’ worker assignment rules will perform well in both environments with and without transfer delays (Malhotra and Kher 1994).

In our model, all idle cross-trained workers join a common list of idle cross-trained workers immediately when they finish their jobs. This common list is managed centrally, assuming that each cross-trained worker can be assigned to a department with zero transfer delay. The assignment of an idle, cross-trained worker from this common list is activated only when there is one or more than one department with waiting job(s), idle machine(s), and no idle primary workers. The first worker in this common list is considered first and assigned to his most proficient department that has at least one waiting job, one idle machine, and no idle primary workers. The next idle, cross-trained worker in this common list is then considered for assignment until there are no available jobs, machines, or idle workers in this common list.

3. Experimental design

The cross-training policies examined in this study can be represented as three factors: (1) number of cross-trained workers, (2) number of additional skills per cross-trained worker, and (3) number of additional machines. These policies are tested and compared in a range of environments represented by (1) efficiency loss, (2) labour utilization, (3) variability in processing times, and (4) worker absenteeism. The cross-training policies and environmental factors are described below.

3.1 Cross-training policies

A total of 16 cross-training policies (i.e. four different numbers of cross-trained workers, two different numbers of additional skills per cross-trained worker, and two different numbers of additional machines) are proposed and examined.

3.1.1 Number of cross-trained workers

With four workers in each department, one, two, three, or four workers from each department can be cross-trained in other departments. This factor is examined to understand the need to cross-train one or more workers since the cost of training more workers must be justified by its benefits. Felan and Fry (2001), for example, have suggested that it is better to cross-train a subset of all workers, while Slomp and Molleman (2002) and Bokhorst *et al*. (2004) have suggested training all workers. This factor is, thus, worth examining.

3.1.2 Number of additional skills per cross-trained worker

A cross-trained worker can be trained to work in one or more additional departments beyond his primary department. Since many past studies have suggested a diminishing return in acquiring more skills, this research examines the breadth of cross-training at two levels. Each cross-trained worker is trained in either one or two additional departments beyond his primary department.

In addition to the above decision on the number of additional skills per cross-trained worker, a decision must also be made on the pattern of cross-training. Two patterns are often cited by past research—block training and chaining (Brusco and Johns 1998, Hopp *et al*. 2004). Block training essentially partitions the workers and departments into blocks. For example, to train six workers with two skills per worker in a six-department job shop, a block training policy would divide the job shop into three blocks, with two workers and two departments in each block. In each block, both workers are trained in both departments in same block. Using the same example, a skill-chaining policy would train each worker with two skills, by training worker 1 in departments 1 and 2, worker 2 in departments 2 and 3, and so on, with worker 6 in departments 6 and 1. Between the two patterns of cross-training, this research uses skill chaining, since it has consistently performed better than block training (Brusco and Johns 1998, Hopp *et al*. 2004).

3.1.3 Number of additional machines

Treleven (1989) has suggested that cross-training workers without the addition of duplicate machines can seriously restrict the deployment of cross-trained workers and thereby limit its benefit. To realize the benefit of cross-training, the addition of duplicate machines is thus an important consideration. When workers are cross-trained, adding spare machines is necessary to provide workers the opportunity to use the extra machines and work in different departments. If no spare machines are added, cross-training, by itself, offers zero benefit.

While past research has suggested that DRC job shops operate best with worker-to-machine ratios from 50% to 75%, no past study has systematically examined when a higher or lower worker-to-machine ratio is desirable. Although a lower worker-to-machine ratio increases the flexibility to deploy cross-trained workers, it also increases the total cost of machines. The cost of adding more machines must thus be balanced with the benefit of a more flexible deployment of cross-trained workers. A careful investigation of this factor is thus important to assess the benefit and cost of adding more machines and to identify the environments where adding more machines is beneficial.

In this study, the number of machines in each department is increased by either one or four machines when cross-training is introduced. In total, we examine two worker-to-machine ratios of 80% and 50% (i.e. four workers/five machines and four workers/eight machines), which cover the range of worker-to-machine ratios cited in past research. Notably, in the base case where cross-training is not practised, all workers work within their own departments and thus do not require any extra machine. The performance of the base case is thus the same, with or without the addition of spare machines.

3.2 Environmental factors

3.2.1 Efficiency loss

The loss of productive time occurs whenever a cross-trained worker works in a department in which he is partially proficient. Past research has used two different methods to model the loss of productive time. One is to model the loss of productive time as a natural process of learning, forgetting, and relearning when workers work in different departments (Kher 2000, Kher and Malhotra 2000, Felan and Fry 2001). Since workers have different experiences working in different departments, they will eventually become more efficient in some departments and less in the others. Loss of productive time thus occurs whenever these workers work in their less proficient departments.

Another way to model the loss of productive time is to assume that each worker has different talents (natural or developed) for different skills. Consequently, each worker is more proficient in some departments and less proficient in the others. Using this method, Bobrowski and Park (1993) and Malhotra and Kher (1994) have represented the workers' ability to work in different departments as an efficiency matrix.

Using both methods of modelling the loss of productive time, past research has not reported any differences in the results. For example, the results of studies by Malhotra and Kher (1994) and by Felan and Fry (2001) are highly consistent, even though they have used different methods to model the loss of productive time. In this research, we therefore choose the simpler method of modelling the loss of productive time using an efficiency matrix.

Efficiency loss is a measure of a worker's mastery of the skills to work in different departments. The efficiency loss of each worker in a cross-trained department is modelled at three levels: 0%, 10%, and 25%. A 0% loss represents a scenario where each worker is 100% (i.e. fully) efficient in all departments in which he is cross-trained. A 10% or 25% efficiency loss represents a scenario where a worker is increasingly less efficient in each additional department in which he is cross-trained. For example, with an efficiency loss of 10%, a worker who is cross-trained in two additional departments will be 100% efficient in his primary department, 90% efficient in the first cross-trained department, and 80% in the second cross-trained department. Consequently, when this worker processes a job in his first cross-trained department, he will need $p/0.9$ time units to finish the job, where p is the processing time if the job is processed by a fully efficient worker.

The presence of efficiency loss will obviously reduce the benefit of cross-training, even though the exact magnitude of its impact and its interactions with different cross-training policies is unknown. For example, when efficiency loss is high, it might be better to train each cross-trained worker with fewer skills so that they can achieve a higher proficiency in each cross-trained department. An examination of different efficiency losses is thus a worthy endeavour.

3.2.2 Labour utilization

Most of the studies on DRC job shops have assumed a mean labour utilization of 90% when cross-training is not practised. In this study, we examine the mean labour utilization at 80%, 90%, and 97%

when cross-training is not practised. These values cover the range of values cited in the literature (Treleven 1989). At 80% mean labour utilization, workers are free 20% of the time when cross-training is not practised. Consequently, there might be little need for flexible capacity or cross-training when labour utilization is low. In contrast, at 97% mean labour utilization, the amount of spare labour capacity in each department becomes scarce at only 3% with no cross-training. Consequently, if cross-training is practised at 97% mean labour utilization, assigning cross-trained workers to less proficient departments can incur a loss of productive time and reduce the limited spare capacity of 3%, and potentially harm performance. At 97% mean labour utilization, cross-training can thus be detrimental. It is therefore interesting to examine the impact of different levels of labour utilization on the benefit of cross-training.

3.2.3 Variability in processing times

Intuitively, the benefit of cross-training depends on the variation of workload across departments. A larger variation in processing times will increase the variation of workload across departments and increase the need to transfer workers from departments with less work to departments with more work. This need for labour transfers will thus, in turn, increase the need for cross-training. While the above argument suggests that increased variability increases the value of cross-training, the magnitude of this benefit is unknown. The impact of variable processing times on each cross-training policy may also be different and is worth investigating. We thus examine three levels of variability in processing times, with the coefficients of variation (CVs) set at 0.0, 0.5, and 1.0. The CV of 0.0 is produced by setting all processing times to a constant. The CVs of 0.5 and 1.0 are produced by generating the processing times using Gamma distributions with different CVs.

3.2.4 Worker absenteeism

To study the impact of worker absenteeism, we consider two cases: 0% and 8.3% worker absenteeism, with 0% representing the base case of no absenteeism. While the presence of worker absenteeism is likely to increase the value of cross-training, its impact on different cross-training policies is not obvious. For example, it might be better to cross-train all workers with equal flexibility when each worker is absent with equal probability. However, when no worker is absent, it might be better to have a mix of some workers with no flexibility and some with a very high flexibility, as suggested by Felan and Fry (2001). Since the goal of this study is to demonstrate only the directional impact of worker absenteeism, we have chosen an absenteeism rate of 8.3%, which lies between the two extremes of 4% and 10% used by Slomp and Molleman (2002) and Bokhorst *et al*. (2004).

When the worker absenteeism of 8.3% is modelled, each worker can be absent on any day with a probability of 8.3%. This absenteeism rate also translates to a mean reduction of 8.3% in labour capacity. The full impact of worker absenteeism is thus a combination of the effects of a reduction and a variation in labour supply. Since the effect of a reduced labour capacity has been modelled above as different levels of mean labour utilization, we choose an environment where management can adjust the mean labour capacity to account for absent workers, e.g. by subcontracting or rejecting some jobs. The mean labour utilization is thus set equal at 90% for both cases of 0% and 8.3% worker absenteeism, by reducing the mean number of new jobs per day from 24 to 22 when the 8.3% worker absenteeism is modelled.

The effect of worker absenteeism in our results thus reports only the effect of the variation in labour supply caused by worker absenteeism. We argue that we have chosen a conservative stance to avoid overstating the impact of absenteeism in environments where management can reduce the workload or increase the labour capacity to account for absent workers. In environments where management cannot adjust the workload or labour capacity to account for absent workers, the full impact of worker absenteeism is a combination of a higher mean utilization of the non-absent workers and a variation in the labour supply.

4. Performance measures

Four performance measures are used to evaluate the effect of the experimental factors. The measures are (1) mean percentage of tardy jobs, (2) mean work in process, (3) mean worker utilization, and (4) mean difference in worker utilization between cross-trained and primary workers.

The mean percentage of tardy jobs (MPTJ) measures the proportion of jobs that finish later than their due dates. This is a measure of customer service. The mean work in process (MWIP) measures the average number of jobs in the job shop, and it is a measure of inventory cost.

The next two measures are of concern to the workers. The mean worker utilization (MWU) is a measure of the proportion of the time when workers are busy. A larger MWU implies less free time for the workers. In the base case where cross-training is not practised, MWU is simply equal to the selected mean labour utilization of 80%, 90%, or 97%. However, when cross-training is practised, the workers must, on average, work longer hours to make up for the loss of productive time that occurs whenever a cross-trained worker is sent to work in a less proficient department. Consequently, when full proficiency cannot be achieved, the MWU with cross-training can be larger than the MWU with no cross-training.

The mean difference in worker utilization between cross-trained and primary workers (MDU) measures the equitability in the distribution of work between cross-trained and primary workers. A smaller MDU thus suggests a fairer distribution of work, even though cross-trained workers are expected to shoulder a heavier load, since they can work in different departments. We also believe that worker assignment rules can significantly affect the balance of work between the primary and cross-trained workers, even though we have fixed the worker assignment rule in this study. An investigation of worker assignment rules on the balance of work is thus suggested for future research.

Before the actual production runs, we conducted several pilot runs. In our pilot runs, we found that the directional impact of each environmental factor on the cross-training policies is unaffected by their interactions. Consequently, to limit the size of the experiment, we propose four independent full-factorial experiments. Table 2 summarizes the factors in the four experimental runs. Each experimental run consists of 16 cross-training policies and one of the four environmental factors, in turn. In each experiment, three of the four environmental factors are fixed. When they are fixed, the efficiency loss is set at 10%, mean labour utilization at 90%, variability in processing times at CV = 0.5, and worker absenteeism at 0%.

The batch means method was used to collect the performance measures. The batch size was chosen for a first-order serial correlation of less than 5% to ensure independence among the batch means (Law and Kelton 1991). Each production run was initialized with a batch size of 40 000 days. Thirty batch means of 20 000 days each were then collected. For each performance measure, analyses of variances were used to identify the significant interactions at a significance level of 1% before they were plotted for further analysis.

Table 2. Experimental design.

Factors	Factor levels
Cross-training configurations	
Number of cross-trained workers	1, 2, 3, and 4
Number of additional skills per cross-trained worker	1 and 2
Number of additional machines per department	1 and 4
Experiment	
Run 1: Efficiency loss	0%, 10%, and 25%
Run 2: Labour utilization	80%, 90%, and 97%
Run 3: Variability in processing times (CV)	0.0, 0.5, and 1.0
Run 4: Worker absenteeism	0% and 8.3%

5. Results

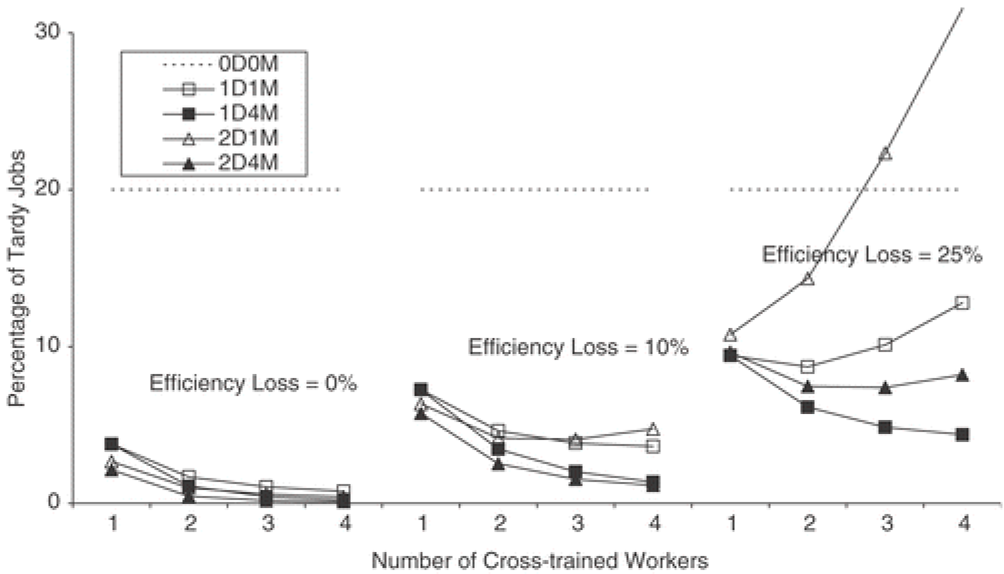
The results on mean percentage of tardy jobs (MPTJ) and mean work in process (MWIP) exhibit a similar pattern. We thus choose not to further discuss the results on MWIP as the discussion on MPTJ also applies to MWIP. The results on mean worker utilization (MWU) are also obvious. For example, MWU increases when the loss of productive time increases as a result of a larger deployment of cross-trained workers across different departments. This happens when cross-training, efficiency loss, variability in processing times, or worker absenteeism increases. We thus discuss only the mean percentage of tardy jobs (MPTJ) and the difference in mean worker utilization between cross-trained and primary workers (MDU).

5.1 Impact of efficiency loss

Figure 1 shows three sub-plots of MPTJ for three levels of efficiency loss. Each sub-plot plots the MPTJ against the number of cross-trained workers per department. The configuration ‘2D4M’, for example, represents the cases of training each cross-trained worker in two additional departments and adding four extra machines in each department. The MPTJ for no cross-training is represented by the dotted line ‘0D0M’, i.e. training workers in 0 additional departments and adding 0 machines in each department.

Figure 1 shows that cross-training is generally beneficial. For example, cross-training just one worker is always better than no cross-training, even when the efficiency loss is as high as 25%. Consistent with past research, Figure 1 shows a diminishing benefit in cross-training more workers and each worker in more departments. Each sub-plot shows that cross-training one or two workers (i.e. 25–50% of all workers) from each department with one additional skill is sufficient to realize most of the reduction in MPTJ.

Figure 1. Impact of efficiency loss on MPTJ.



The benefit of cross-training relative to no cross-training can be viewed as the gap between the set of cross-training policies (represented by lines 1D1M, 1D4M, 2D1M, and 2D4M) and no cross-training (represented by the dotted line 0D0M). Figure 1 shows that this gap (i.e. the difference in MPTJ between cross-training and no cross-training) decreases as efficiency loss increases. The benefit of cross-training hence becomes smaller when workers do not have the natural or developed ability to achieve full or high proficiency in their cross-trained departments.

The sub-plot for zero efficiency loss shows that training each cross-trained worker in more departments consistently produces a smaller MPTJ. However, when the efficiency loss increases to 25%, training each cross-trained worker in two additional departments produces a larger MPTJ than training them in one additional department. A positive efficiency loss implies that a worker is increasingly less proficient in each additional skill in which he is cross-trained. When efficiency loss is large, cross-trained workers therefore incur a much larger loss of productive time, especially when they are sent to work in their least proficient departments. Consequently, when workers are unable to master the additional skills well, it is better to train them in fewer skills and avoid training them incompetently in too many skills.

Similarly, it is also better to cross-train fewer workers than all workers when they are unable to master the additional skills well. For example, the subplot for 25% efficiency loss in Figure 1 shows that the MPTJ of ‘2D1M’, ‘1D1M’, and 2D4M’ increases when the number of cross-trained workers increases beyond 2. Intuitively, when workers are unable to master the additional skills well, cross-training more workers increases the number of incompetent workers competing for spare machines. This, in turn, increases the chance of sending them to their less proficient departments and increases the loss of productive time and MPTJ.

Each sub-plot in Figure 1 also shows that adding four machines in each department always produces a smaller MPTJ than adding one machine, i.e. 1D4M and 2D4M consistently produce a smaller MPTJ than 1D1M and 2D1M, respectively. While the gap between 1D1M and 1D4M (also 2D1M and 2D4M) is statistically insignificant (all statistical tests were conducted at a significance level of 1%) when the efficiency loss is zero, the gap increases and becomes statistically significant when the efficiency loss increases to 10% and 25%. For both efficiency losses of 10% and 25%, the difference in MPTJ between adding one and adding four machines also increases when the number of cross-trained workers per department increases and when each cross-trained worker is trained in more departments. Consequently, when efficiency loss is significant (i.e. 10% or more), adding more machines is highly beneficial for a large team of highly cross-trained workers to increase the chance of matching the workers to their most proficient departments and avoid the loss of productive time of sending them to their less proficient departments.

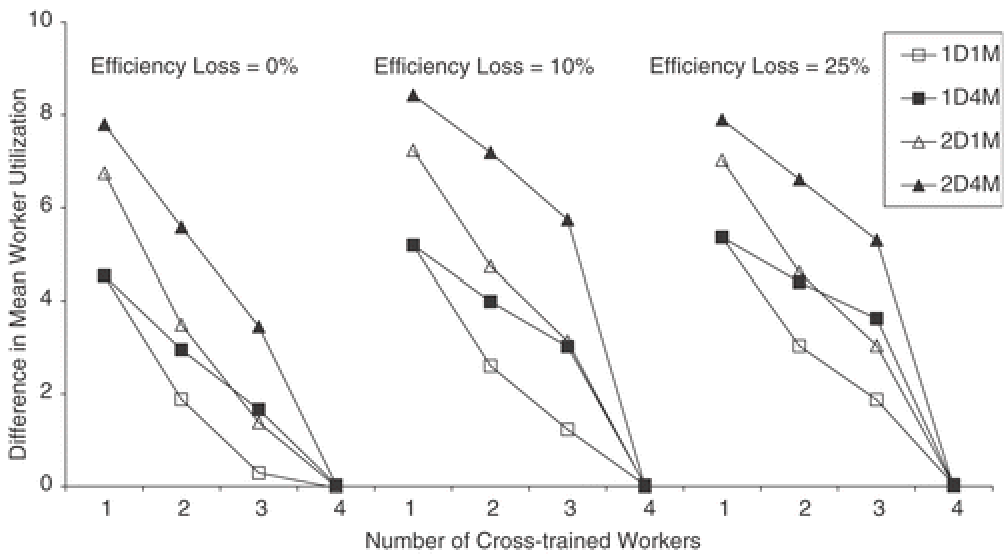
Figure 1 also shows an interesting result that contradicts the finding of Felan and Fry (2001). In their article, Felan and Fry (2001) suggested that 'it is better to have a mix of workers with no flexibility and some workers with very high flexibility rather than all workers with equal flexibility'. In contrast, for our job shops with a total of four additional skills per department, Figure 1 shows that cross-training all four workers per department with one additional skill always produces a smaller MPTJ than cross-training two workers per department with two additional skills. In addition, for job shops with a total of two additional skills per department, Figure 1 shows that cross-training two workers per department with one additional skill is also consistently better than cross-training one worker per department with two additional skills. In other words, for a fixed total number of additional skills, our results show that it is always better to spread the skills across more workers than to cross-train a smaller group of workers with more skills. This observation contradicts the finding of Felan and Fry (2001), and the difference is explained in the next paragraph.

The difference in the results observed by Felan and Fry (2001) and by this study can be explained by the different 'where' worker assignment rules used to assign cross-trained workers to different departments. In their study, 2001) assigned cross-trained workers to departments with longest queues. Consequently, when all workers are cross-trained, many can be assigned to their less proficient departments incurring large losses of productive time. In contrast, a job shop with a mix of workers with no flexibility and some workers with very high flexibility can, at least, reduce some of the losses of productive time, by confining the workers with no flexibility in their most proficient departments. This observation thus suggests that a job shop with all workers cross-trained can do better if a more effective 'where' rule is used to match each worker to the 'right' machine and avoid the unnecessary loss of productive time. Our results thus show that by assigning cross-trained workers to their most proficient departments, a team of equally cross-trained workers can produce a smaller MPTJ than a mix of workers with no cross-training and some workers with very high cross-training.

Figure 2 shows three sub-plots of MDU for three levels of efficiency loss. Each sub-plot shows a similar pattern, suggesting that efficiency loss does not significantly affect the behaviour of MDU. (The other three environmental factors—labour utilization, variability in processing times, and worker absenteeism—also produce similar patterns of MDU. The discussions on MDU for efficiency loss thus also apply to the other three environmental factors and are not repeated.) Each sub-plot shows the MDU decreases when the number of cross-trained workers per department increases and when each cross-trained worker is trained in fewer departments. These results are intuitive. Cross-training more workers produces more cross-trained workers to share the workload variation across departments and, hence, improves the equitability in the workload shouldered by the cross-trained and primary workers. Similarly, training each cross-trained worker with fewer skills reduces their flexibility to do more than the primary workers and improves the equitability in the workload shared by the cross-trained and primary workers. Training each cross-trained worker with one additional skill is thus highly recommended. It not only realizes most of the improvement in MPTJ but also provides the best equity in the workload distribution between cross-trained and primary workers.

Each sub-plot in Figure 2 also shows that adding four machines in each department produces a larger MDU than adding one machine, i.e. 1D4M and 2D4M produce larger MDU than 1D1M and 2D1M, respectively. This result is not surprising, since adding more machines increases the number of spare machines available to the cross-trained workers and keeps them busier whenever there are waiting jobs in their cross-trained departments. Adding more machines thus makes the cross-trained workers busier than the primary workers.

Figure 2. Impact of efficiency loss on MDU.

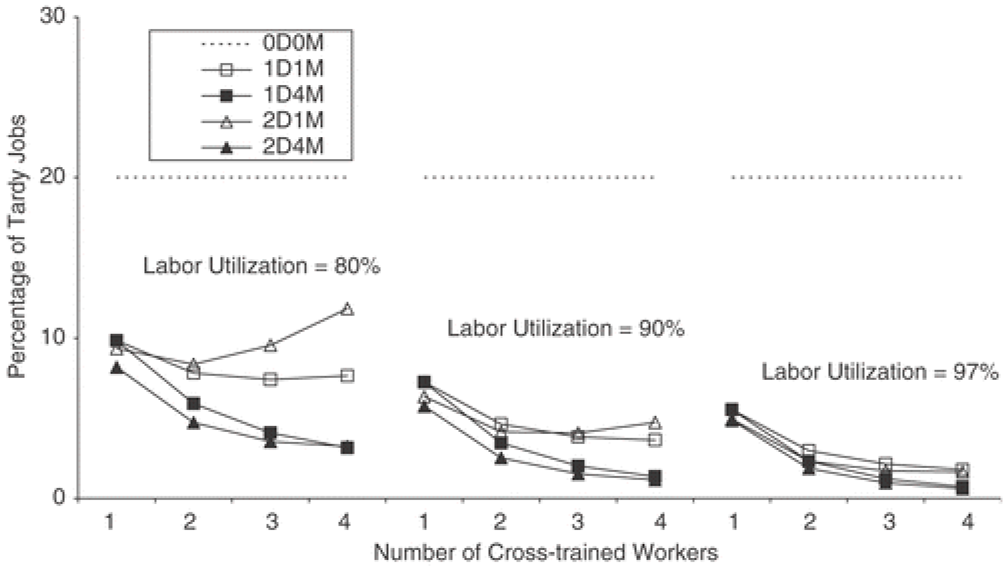


5.2 Impact of labour utilization

Figure 3 shows three sub-plots of MPTJ for three levels of mean labour utilization. Each sub-plot shows an increasing gap between cross-training and no cross-training as mean labour utilization (without cross-training) increases from 80% to 97%, i.e. the gap between the lines represented by 1D1M, 1D4M, 2D1M, and 2D4M and the dotted line represented by 0D0M. The benefit of cross-training in reducing the MPTJ thus increases in job shops with busier workers. This is an interesting result because even though cross-training incurs lost productive time as a result of efficiency loss, it continues to improve the MPTJ when mean labour utilization (without cross-training) is as high as 97%.

Similar to the results in Figure 1, Figure 3 shows that most of the improvement in MPTJ can be achieved by cross-training one or two workers from each department with one additional skill. Each sub-plot also shows that adding four machines consistently produces a smaller MPTJ than adding one machine. This gap between 1D1M and 1D4M (and also 2D1M and 2D4M) is, however, statistically insignificant when the mean labour utilization is 97%. The gap becomes statistically significant only when the mean labour utilization decreases to 90% and 80%.

Figure 3. Impact of labour utilization on MPTJ.

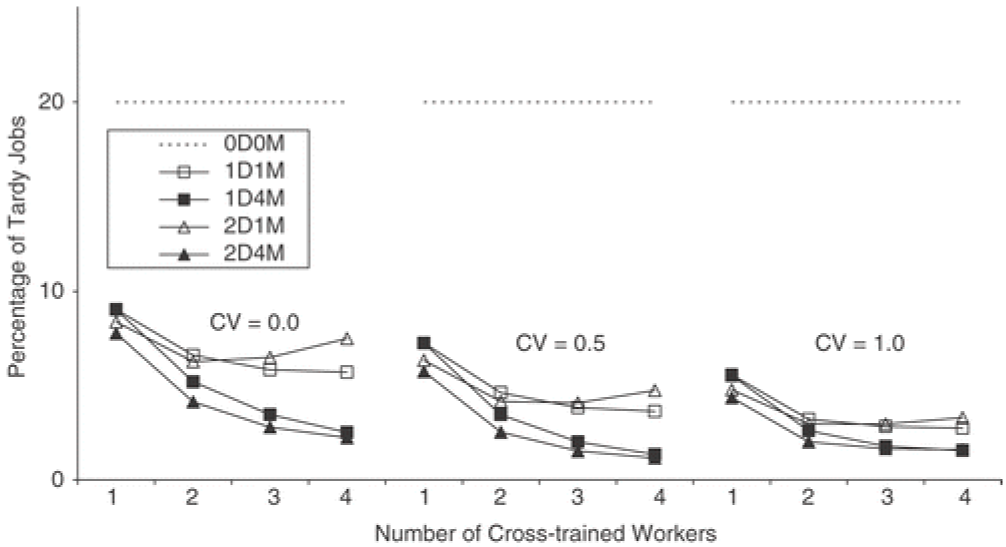


Adding more machines is thus significantly more beneficial when the mean labour utilization is low (e.g. 80% and 90%). When the mean labour utilization is low, there is a longer list of idle cross-trained workers, waiting for the ‘right’ machines, blocking each other's access to their most proficient machines and hurting the performance. When the mean labour utilization is low, Figure 3 shows that cross-training more workers and each worker in more skills can produce a larger MPTJ when the number of extra machines is insufficient. For example, the sub-plots for 80% and 90% mean labour utilization show that the MPTJ of the policy ‘2D1M’ increases when the number of cross-trained workers increases beyond 2, while the MPTJ of ‘2D4M’ continues to improve beyond three and four cross-trained workers. Adding more machines at a low mean labour utilization thus ensures that the cross-trained workers, who are idle more frequently and in larger number at the same time, have more machines to work on and a greater opportunity to work on their most proficient machines.

5.3 Impact of variable processing times

The MPTJ for different levels of variability in processing times is plotted in Figure 4. As the variability in processing times increases, the gap between cross-training and no cross-training increases. Since the need to assign cross-trained workers across departments increases with a greater variability in processing times or workload across departments, it is not surprising that cross-training is more beneficial when processing times are more variable.

Figure 4. Impact of variable processing times on MPTJ.



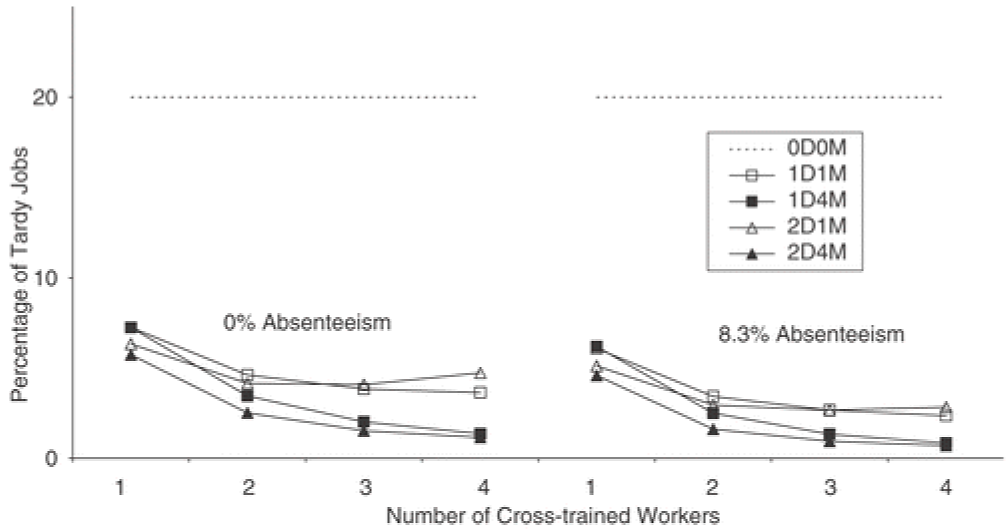
Each sub-plot shows that adding four machines in each department produces a smaller MPTJ than adding one machine. A comparison of the three subplots suggests that adding more machines is significantly more beneficial when the processing times are less variable. When processing times are less variable, there are, on average, a larger number of idle cross-trained workers waiting for jobs and machines at the same time. Adding more machines when processing times are less variable thus provides the longer list of idle cross-trained workers with more machines to work on and a greater opportunity to match workers to their most proficient machines whenever jobs appear.

5.4 Impact of worker absenteeism

Figure 5 plots the MPTJ as two sub-plots, representing the cases of 0% absenteeism and 8.3% absenteeism. The difference in MPTJ between cross-training and no cross-training is larger with worker absenteeism. The benefit of cross-training on MPTJ is thus larger when there are absent workers. This is not surprising, since worker absenteeism increases the need for labour transfers which, in turn, increases the need for and value of cross-training.

At each worker-to-machine ratio (i.e. adding one or four machines), the number of machines available per *non-absent worker* is larger when absenteeism occurs. The need for more machines (i.e. adding four instead of one machine) is therefore less important when there is absenteeism. Figure 5 thus shows that the incremental improvement in MPTJ is larger for zero absenteeism versus 8.3% absenteeism when the number of extra machines is increased from one to four. On average, the scenario of zero absenteeism has more workers present in the job shop than the scenario of 8.3% absenteeism. Adding more machines when no workers are absent thus provides the idle cross-trained workers, who are in larger number on average, with more machines to work on and a greater opportunity to work on their most proficient machines.

Figure 5. Impact of worker absenteeism on MPTJ.



6. Conclusions

This research examines the performance of a set of cross-training policies represented by different numbers of cross-trained workers, additional skills per cross-trained worker, and additional machines. The cross-training policies are examined in a range of job shops represented by different efficiency losses, labour utilization, variability in processing times, and worker absenteeism. The results offer several insights on the value of cross-training and adding machines in different job shops.

Consistent with past research, our results show a diminishing benefit in cross-training more workers and each worker in more skills. Similarly, there is also a diminishing benefit in adding more machines. In particular, when efficiency loss is high, the loss of productive time is large when cross-trained workers are sent to work on their less proficient machines. Hence, when efficiency loss is high, excessive cross-training of too many incompetent workers in too many skills can increase the incidents of incompetent workers sent to the ‘wrong’ machines and, in turn, increase the mean percentage of tardy jobs and work in process relative to less or no cross-training.

Nevertheless, our results show that adding one machine in each department and cross-training one or two workers (i.e. 25–50% of all workers) from each department with one additional skill is generally sufficient to realize most of the benefit of cross-training. Cross-training is thus beneficial in most job shops except for cases where the cost is high, even for minimal cross-training and a few extra machines.

While cross-training workers in job shops with spare machines is generally beneficial, the size of its benefit depends very much on the environment. Significantly larger improvements are reported in environments with low efficiency loss, high labour utilization, high variability in processing times, and high worker absenteeism. Cross-training is thus highly recommended in the above environments.

The value of adding spare machines also depends on the environment and the level of cross-training. While adding one machine per department is sufficient when one or two workers from each department are cross-trained with one additional skill, the addition of more machines is beneficial when there are more cross-trained workers and workers cross-trained with more skills. In particular, when the efficiency loss is significant (e.g. 10% or more), adding more machines is beneficial when there is a long list of cross-trained workers waiting for the ‘right’ machines. This occurs in environments with low labour utilization, low variability in processing times, or low worker absenteeism. Adding more machines in these environments mitigates the loss of productive time by increasing the chance of matching cross-trained workers with their most proficient machines and by reducing the chance of blocking workers, ranked lower in the common list, from working at their most proficient machines. Similarly, if machines are expensive or cannot be added, cross-training should be limited to avoid having a long list of cross-trained workers blocking each other's access to their most proficient machines.

Finally, our results show that for a fixed total number of skills, it is always better to spread the skills over more workers than to cross-train a few workers with more skills. Using the ‘where’ rule of assigning workers to their most proficient departments, our results show that a team of workers with equal flexibility always performs better than a mix of workers with no flexibility and some workers with a very high flexibility.

There are many opportunities for future research on DRC job shops. Future research, for example, can vary and re-examine some of the fixed factors in this study. An investigation of different worker assignment rules and their impact on balancing the utilization of primary and cross-trained workers could also be an interesting study. Future research can also examine job shops with bottlenecks to better define the distribution of cross-training between bottleneck and non-bottleneck departments.

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