

University of Groningen

Shop floor design

Bokhorst, J.A.C.

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version

Publisher's PDF, also known as Version of record

Publication date:

2005

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Bokhorst, J. A. C. (2005). *Shop floor design: layout, investments, cross-training, and labor allocation*. [Thesis fully internal (DIV), University of Groningen]. s.n.

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Chapter 3

Cross-training

CROSS-TRAINING IN A CELLULAR MANUFACTURING ENVIRONMENT³

Jannes Slomp, Jos A.C. Bokhorst and Eric Molleman

ABSTRACT

This study addresses the need for cross-training in a cellular manufacturing environment. It is demonstrated that an effective cross-training situation results if workers and machines are connected, directly or indirectly, by task assignment decisions. The connections between workers and machines (i.e. the qualifications of workers) form “chains” that can be used to reallocate work from heavily loaded workers to less loaded workers. This provides the possibility of a balanced workload situation among workers, something that is desirable from a social as well as an economic viewpoint. Based on this insight, we have developed an integer programming (IP) model that can be used to select workers to be cross-trained for particular machines. The model may help in trade-offs between training costs and the workload balance among workers in a manufacturing cell. The workload balance indicates the usefulness of labor flexibility in a particular situation. A numerical example is presented to illustrate various elements and features of the model. It also provides further insight into the role of “chaining” workers and machines. The industrial applicability of the model and directions for future research are also indicated.

Key words: Cellular Manufacturing, Teams, Labor Flexibility, Training Costs

1. Introduction

A manufacturing cell may be defined as the grouping of people and processes, or machines, into specific areas dedicated to the production of a family of parts. A manufacturing cell requires a cross-trained workforce in order to deal with variations in the demand mix and/or fluctuations in the supply of labor (see e.g. Molleman and Slomp, 1999). Cross-training also implies labor flexibility that, on condition that there are appropriate operating rules, has a positive effect on operational performance indicators, such as the throughput time and the delivery performance of jobs (see e.g., Treleven, 1989). Cross-training also increases the possibility that workers may help each other and share their workloads, thus enhancing feelings of interpersonal justice and equity (e.g. Austin, 1977). This paper concentrates on the question “to what extent should the labor force in a manufacturing cell be cross-trained?” and, more specifically, on the question “who should be cross-trained for which machine?” The relevance of these questions will be explained in this introductory section.

³ This paper is in press for Computers & Industrial Engineering.

Several authors have studied the topic of labor flexibility over the years. It has been shown repeatedly that increases in labor flexibility positively affect system performance. Most of the positive effects are achieved without going to the extreme of total flexibility. Several authors have noted in recent years that limited amounts of cross-training are sufficient to gain near optimal performance results (see e.g. Park and Bobrowski, 1989, Fry *et al.* 1995, and Molleman and Slomp, 1999). Total flexibility of the workforce is not needed nor is it desirable in practical situations. That would require training all workers for all machines, which would be very costly. A high level of labor flexibility may also involve considerable productivity loss due to the shift of workers between machines. Among other losses, this productivity loss concerns the required orientation time at new work stations, the time needed to access information about processing jobs at the new machine and the time needed to learn or relearn the setup procedures. Kher and Malhotra (1994) have shown that a higher level of labor flexibility will lead to more labor shifts. This is especially the case if the firm applies a centralized assignment rule (i.e., a worker shift is considered after completion of each job). The effect is less in the case of a decentralized rule, i.e., where a worker shift is considered only when the job queue is empty. In both cases, however, productivity loss due to an increase in the number of worker shifts is an argument to limit the level of labor flexibility.

There are also several social arguments for limiting labor flexibility in manufacturing cells (see e.g. Van den Beukel and Molleman, 1998). High levels of labor flexibility may impair social identity because the different jobs in a team/cell will be more similar. This may cause motivational deficits (Fazakerley, 1976). With respect to their abilities, people may prefer diversity within the team/cell. Being a specialist enhances feelings of being unique and indispensable and makes the contribution to group performance visible (Clark, 1993). In addition, studies pertaining to diversity reveal that creativity and motivation are greater in teams whose members have different –but somewhat overlapping– skills (e.g., Jackson, 1996). High levels of labor flexibility may also cause social loafing and, for example, cause a situation in which no one is willing to do the dirty work (Wilke and Meertens, 1994). Cross-training may also lead to perceived lowering of status differentials within teams, which may result in negative attitudes, particularly among the higher-status team members who oppose learning and performing the lower status jobs (Carnall, 1982; Cordery, Sevastos, Mueller and Parker, 1993; Hut and Molleman, 1998).

The above arguments against striving for full flexibility in a manufacturing cell raise the questions as to what extent the labor force should be cross-trained and, more precisely, who should be cross-trained for which machine. These questions are as yet unresolved (see e.g. Treleven, 1989 and Pennathur *et al.*, 1999). Few analytical studies that help to answer these questions have been performed. Stewart *et al.* (1994) presented four integer programming models for developing a flexible workforce. These models attempted to minimize the total cost of training, to maximize the flexibility of the workforce, to minimize the total time required for training, and to optimize the trade-off between training costs and workforce flexibility. The model formulations force an optimal assignment of tasks (hours) to workers. Important constraints in the models are the production hours available, the production requirements, and the budget for training. Although the models of Stewart *et al.* (1994) provide a valuable reference for developing a mathematical formulation, there are some significant pitfalls in them. One of their assumptions is that it is not necessary to balance assignments among workers. In section 2 of this paper we will show that this assumption may lead to a situation in which one or more workers depress the performance

of the manufacturing cell. The models of Stewart *et al.* (1994) also do not incorporate the issue of fluctuations in the demand and or supply of labor.

Brusco and Johns (1998) presented a linear programming model that minimizes workforce staffing costs subject to the satisfaction of minimum labor requirements across a planning horizon. They used the model to evaluate eight cross-training structures across various labor requirement patterns. An important result of their study concerned the conclusion that “chaining of employee skill classes across work activity categories” is a basic element of successful cross-training structures. Chaining enables work to be shifted from a heavily loaded worker to a less loaded worker, directly or indirectly, leading to a more balanced workload. This supports the efficient use of labor capacity. Further, workers may perceive a balanced workload as fair. Our model builds further on this result. Molleman and Slomp (1999) presented a mathematical model to assign multi-skilled workers to the various tasks (or machines) in a team. They studied the effect of labor flexibility on team performance. Team performance is measured as the shortage of labor capacity (i.e. no capable worker is present to perform a particular task), the minimum time needed to perform all tasks (i.e. the load of the bottleneck worker), and the cumulative time needed to perform all tasks. Important conditions that affect the required level of labor flexibility include demand variation and worker absenteeism. Molleman and Slomp (1999) showed that a uniform distribution of multifunctionality among the workers provides the best team performance. They also indicated that absenteeism should be regarded as a major reason to invest in labor flexibility. As a general statement, they suggested that each task should be mastered by at least two workers in order to reduce the negative impact of low to moderate levels of absenteeism. Above this minimal level of flexibility, labor flexibility needs to covary with the demands on capacity for each task. Although the model of Molleman and Slomp (1999) provides some general guidelines, it does not give detailed suggestions with respect to cross-training. The model presented in this paper may be regarded as a useful extension of their model.

Some authors propose that labor issues should be taken into account at the cell design stage. Min and Shin (1993) and Suresh and Slomp (2001) propose cell design procedures in which the complex cell formation problem is solved in two or more phases. The last phase in both procedures concerns labor issues. A basic assumption in the problem formulation of Min and Shin (1993) is that operators are linked with the various parts by means of so-called “skill matching factors”. A skill matching factor indicates to what extent a worker is able to produce a part. These factors are used for the optimization of the operator assignment problem. Cross-training issues were not considered in this work. Suresh and Slomp (2001), in the last phase of their procedure, address various labor issues such as the partitioning of functionally specialized labor pools and the required additional training of workers. The need for cross-training is predetermined in their approach by setting minimum and maximum levels for the multifunctionality of workers and the redundancy of machines. They do not analytically determine the need for cross-training. Süer (1996) presented a two-phase hierarchical methodology for operator assignment and cell loading in labor-intensive manufacturing cells. Here, the major concern is the determination of the number of workers in each cell and the assignment of workers to specific operations in such a way that worker productivity is maximal. A functional arrangement of tasks was assumed in each cell without considering training and multifunctionality problems. Askin and Huang (2001) focused on the relocation of workers into cells and the training needed for effective cellular manufacturing. They proposed a mixed integer, goal-programming model for guiding the worker assignment and training process. The model integrates psychological, organizational, and technical factors. They

presented greedy heuristics as a means to solve the problem. Askin and Huang (2001) assumed that the required skills are cell dependent and that workers may need some additional training, again without considering cross-training issues. Norman *et al.* (2002) presented a mixed integer programming formulation for the assignment of workers to operations in a manufacturing cell. Their formulation permits the ability to change the skill levels of workers by providing them with additional training. Training decisions are taken in order to balance the productivity and output quality of a manufacturing cell and the training costs. Norman *et al.* (2002) did not deal with the need for cross-training either. Our approach, presented in this paper, is explicitly focused on gaining sufficient cross-training in a manufacturing cell in order to be able to deal effectively with all kinds of fluctuations. It covers an additional aspect of the design of human arrangements in cellular manufacturing systems, in comparison with other contributions. Our approach fits in the last phase of integrated cell formation procedures, as do the formulations of Askin and Huang (2001) and Norman *et al.* (2002). It should, however, be noted that the methodology is also useful during the life cycle of a manufacturing cell. Manufacturing cells are subject to change over the course of years due to new technology, market changes and worker attrition (see Molleman *et al.*, 2002). These changes may lead to new training programs for workers.

Our study concerns the need for cross-training of workers in manufacturing cells. In order to select workers to be trained for certain machines, we will take into account the training costs as well as the efficiency that a worker can realize while operating a particular machine after training. Efficiency is defined in our study as the relative speed by which tasks can be performed by workers. This definition conforms with several other studies (e.g. Brusco *et al.*, 1998, and Bobrowski and Park, 1993). The efficiency of a worker at a machine depends on the speed that the worker can perform manual tasks such as machine setups and quality checks. The variety of efficiency levels of the various workers at a particular machine depends on the labor intensiveness of the tasks involved. Highly automated machines may result in less variety in the efficiency levels of operators. We assume in this paper that additional training cannot further influence the efficiency level of a worker at a particular machine; the efficiency level is already at the end of the worker's learning curve. An Integer Programming Model has been formulated to solve the selection problem. The result of this exercise may be a useful input for developing a training program for workers in teams or manufacturing cells.

In the next section we describe the problem in more detail and explore ways of solving it. In section 3, we give a problem definition, where the parameters and variables we use in our model are explained. In section 4 the model itself is presented. Section 5 explains the working of the model by means of an illustrative example. Section 6 discusses the applicability of the model and makes suggestions for further research.

2. Basic considerations

Figure 1a presents an example of a worker-machine matrix. The figure reveals which workers can operate which machines, denoted by an X. Multifunctionality is defined as the number of different machines that a worker is able to cope with, and redundancy is defined as the number of workers that can operate a specific machine (Molleman and Slomp, 1999).

M\W	A	B	C	D	Dm
1	X(12)	X(0)			12
2	X(0)	X(14)			14
3	X(6)	X(4)			10
4			X(10)	X(0)	10
5			X(0)	X(6)	6
6			X(2)	X(6)	8
WL	18	18	12	12	

(a)

M\W	A	B	C	D	Dm
1	X (6)	X (6)			12
2	X (7)	X (7)			14
3	X (2)		X(8)		10
4		X(2)		X (8)	10
5			X (3)	X (3)	6
6			X (4)	X (4)	8
WL	15	15	15	15	

(b)

(M = machine; W = worker; an X means that worker W is qualified to operate machine M; WL = workload; Dm = demand)

Fig.1. Examples of machine-worker matrices

The multifunctionality of each worker in the example in figure 1a is three, while the redundancy of each machine is two. As can be seen, the manufacturing cell team consists of two independent subgroups, each with two workers. Figure 1a illustrates how the demand for each machine can be assigned to the various workers. As shown, the workloads of the subgroups differ substantially due to the distribution of skills among the workers. In the example in figure 1a, it is not possible to shift work from the first subgroup to the second, thus balancing the workload. In the event of a set of dependent tasks, the subgroups cannot be treated as independent and the most heavily loaded subgroup will be the bottleneck and thus determine the output of the whole team. The distribution of skills in figure 1a, therefore, is not optimal. To be better able to balance the workload, the skills should be distributed differently, eliminating subgroups. An example is presented in figure 1b. Here, although the redundancy of the machines is still two and the multifunctionality of the workers is still three, the workload can be balanced among the workers. This is due to the fact that a possibility to shift work between the workers of the manufacturing cell has been created. Workers and machines are “chained” in the situation in figure 1b by means of their qualifications. Jordan and Graves (1995) stress the importance of chaining in the case of limited flexibility. They have studied the effect of process flexibility, which in their study is the ability of plants to produce different types of products. This type of flexibility is conceptually equivalent to labor flexibility, that is, the ability of workers to operate

different machines. Brusco and Johns (1998) have recognized this and use the term “chaining” to explain the preference of some of their cross-training patterns. Chaining eliminates the existence of the subgroups. Chaining will also prevent the emergence of subgroups that may cause inter-group conflicts and lead to the disintegration of a team (see Wilke and Meertens, 1994). In terms used by Lau and Murnighan (1998), a distribution of skills as depicted in figure 1a will be a potential “faultline” in the team.

It is now clear that the distribution of redundancy and multifunctionality is important when developing a training program. Cross-training in teams/cells has to be performed in such a way that a balanced workload can be realized. Seen the other way around, a balanced workload requires a certain level and distribution of skills. This observation has been used to develop the integer programming (IP) model presented in this paper.

It should be noted that the situation in figure 1 assumes a certain number of workers and a particular demand situation. As mentioned earlier, labor flexibility is needed to cope with variations in the demand mix and fluctuations in the labor supply. This means that the mathematical model to be developed should cope with the cross-training problem under various circumstances.

3. Problem definition

Notation

Index sets:

$\{k=0, \dots, K\}$	=	Index set of demand situations
$\{l=0, \dots, L\}$	=	Index set of labor supply situations
$\{i=1, \dots, I\}$	=	Index set of machines
$\{j=1, \dots, J\}$	=	Index set of workers

Parameters:

$\{A_l\}$	=	Set of absent workers in labor supply situation l
TC_{ij}	=	Training costs for operator j for machine i
MC_{ij}	=	Maintenance costs for operator j for machine i
D_{ik}	=	Demand for machine i in demand situation k
c_{kl}	=	Factor to translate the workload of the bottleneck worker in each situation (k, l) into periodic costs
c_{ij}	=	Factor to translate the training costs of worker j for machine i into periodic costs
e_{ij}	=	Inefficiency factor for machine i when performed by worker j
R_i^+	=	Maximal redundancy for machine i
R_i^-	=	Minimal redundancy for machine i

M_j^+	=	Maximal multifunctionality for worker j
M_j^-	=	Minimal multifunctionality for worker j
π_1, π_2	=	Weight factors
Ω	=	Constant (large value)

Variables:

WB_{kl}	=	Load of the bottleneck worker for situation (k, l)
x_{ijkl}	=	Normalized time assigned to worker j to operate machine i in situation (k, l)
y_{ij}	=	1, if worker j has to be trained for machine i ; 0, if not

The basic assumption in our approach is that training should lead to a situation in which all workers can be equally loaded in various circumstances. If that is the case, then there will be no subgroups under any of these circumstances or, in other words, there is always the possibility of “chaining”. Within an integer programming (IP) formulation, equally loaded workers can be realized through minimizing the load of the bottleneck worker, thus forcing one or more workers to be trained for particular machines. The load of the bottleneck worker is defined as the minimal time needed by the workers to finish all the work. The worker with the heaviest workload determines this time. In a completely balanced situation, all workers are bottleneck workers.

The machines in the manufacturing cell are denoted by the index set $\{i=1, \dots, I\}$, and the workers are denoted by the index set $\{j=1, \dots, J\}$. We specify a number of situations to model the variations in demand for each machine and the fluctuations in the labor supply. In each demand situation, given by the index set of $\{k=0, \dots, K\}$, the demand for machine i equals D_{ik} . In each labor supply situation, given by the index set of $\{l=0, \dots, L\}$, one or more persons may be absent. In situation l , the workers of set $\{A_l\}$ are absent. All situations L and K cover what management regards as situations that need to be dealt with by the particular team/cell, without considering interventions such as working overtime and subcontracting certain tasks. WB_{kl} denotes the load of the bottleneck worker for situation (k, l) . In a balanced situation, WB_{kl} equals the workload of all workers in situation (k, l) .

The training costs of worker j for machine i are denoted by TC_{ij} . It will be clear that the training costs are zero for a worker who is already qualified to operate the particular machine. Each worker can be given an inefficiency factor for each machine, denoted by e_{ij} . If $e_{2,1}$ equals 1.05, for example, then worker 1 will operate machine 2 five percent slower than the normalized time for operating machine 2, after training. The factor e_{ij} enables us to distinguish workers who are not equally efficient in performing the various tasks. This is especially relevant in human paced task environments.

In the model we have set boundaries on the redundancy per machine and the multifunctionality per worker. The maximum redundancy of machine i is given by R_i^+ and the minimum redundancy by R_i^- . These boundaries enable redundancy constraints to be set for particular machines. Critical machines that are needed for each customer and/or product, for instance, may demand a high minimum redundancy in order to anticipate the departure of workers from the team. A maximum redundancy may be set for machines that are sensitive to change and will be altered in the course of time. Boundaries for the multifunctionality of workers are given by M_j^+ for the maximum multifunctionality and M_j^- for the minimum multifunctionality of worker j . Some people are more ambitious than others and like to be able to operate many machines. They may “fly” over the shop floor and stand in wherever they are needed. Others feel most comfortable when they are operating their favorite machine.

Let y_{ij} be a binary variable that equals 1 if worker j has to be trained to perform machine i , and 0 otherwise. The normalized time assigned to worker j to operate machine i in situation (k, l) is denoted by x_{ijkl} . The objective of the model presented in the next section is to determine which workers should be trained for which machines.

4. The Model

The Integer Programming Model presented below calculates which workers have to be trained for which machines so that absenteeism becomes manageable, fluctuations in demand can be dealt with, and the available skills can be applied as efficiently as possible. Further, training costs can be minimized and constraints concerning a maximum and minimum amount of multifunctionality and redundancy can be formulated. This has resulted in the following integer programming model:

$$\text{Minimize } \pi 1 \sum_k \sum_l c_{kl} WB_{kl} + \pi 2 \sum_i \sum_j c_{ij} TC_{ij} y_{ij}$$

subject to:

$$D_{ik} - \sum_j x_{ijkl} \leq 0 \quad \forall i, k, l \quad (1)$$

$$\sum_i e_{ij} x_{ijkl} \leq WB_{kl} \quad \forall j, k, l \quad (2)$$

$$x_{ijkl} \leq \Omega y_{ij} \quad \forall i, j, k, l \quad (3)$$

$$\sum_j y_{ij} \leq R_i^+ \quad \forall i \quad (4)$$

$$\sum_j y_{ij} \geq R_i^- \quad \forall i \quad (5)$$

$$\sum_i y_{ij} \leq M_j^+ \quad \forall j \quad (6)$$

$$\sum_i y_{ij} \geq M_j^- \quad \forall j \quad (7)$$

$$x_{ijkl} = 0 \quad \text{if } [j \in A_l] \quad \forall i, j, k, l \quad (8)$$

$$x_{ijkl} \geq 0 \quad \forall i, j, k \quad (9)$$

$$y_{ij} = 0 \text{ or } 1 \quad \forall i, j \quad (10)$$

The objective function concerns a tradeoff between the operating costs of the manufacturing cell and the costs of cross-training. The first part of the objective function concentrates on the minimization of the periodic (e.g. annual) operating costs of the system. We assume that the operating costs incurred in each period are linearly related to the workload of the bottleneck worker. This assumption is based on the idea that the bottleneck worker determines the efficiency of the manufacturing cell. That is, the load of the bottleneck worker may be seen as a lower bound on the makespan of all jobs included in the model. If the bottleneck load can be decreased, the manufacturing cell will be able to deliver the same set of jobs within a shorter amount of time. This creates the possibility to attract more work and decrease unit operating costs. Because of job interaction and labor blocking, the minimal makespan for which a feasible schedule can be realized will often be greater than the lower bound (see e.g. Raaymakers and Fransoo, 2000). A minimal lower bound, however, is positively related to the minimum makespan that can be realized, since both the lower bound and the minimum makespan depend on the flexibility gained by chaining workers and machines and the utilization of workers at their highest efficiency. WB_{kl} is the workload of the bottleneck worker in situation (k, l) , assuming that all the demand has to be performed in this situation. The parameter c_{kl} transfers WB_{kl} into the periodic (e.g. annual) production costs due to the temporal existence of situation (k, l) . The value of c_{kl} equals the multiplication of the costs per “bottleneck hour” in situation (k, l) times the relative presence of this situation.

The second part of the objective function is focused on minimizing the training costs for the workers. The parameter c_{ij} converts the training costs into periodic (annual) costs. The value of c_{ij} depends on the desired payback period for the training costs spent on teaching machine i to worker j . The desired payback period is obviously short for machines that will change in the near future. It is also conceivable that the desired payback period may vary per worker. The use of the concept of “payback period” for training costs is based on the consideration that cross-training is only valuable for a certain period of time, because of the risk of workers leaving the company and the need for new skills due to new manufacturing technology.

There are two weight factors in the objective function, π_1 and π_2 . If these factors have the value 1, the objective function will minimize total costs per period. Other arguments may lead to other settings for the weight parameters π_1 and π_2 . It is, for instance, likely that the load of the bottleneck worker (WB_{kl}) is related to performance factors such as due date performance and manufacturing flexibility. We expect that the lower the load of the bottleneck worker is, the better the performance on non-cost performance indicators will be. This expectation may lead to higher values for π_1 . Limitations to the training budget may lead to higher settings for the values for π_2 .

The objective function may also be seen as a tradeoff between flexibility advantages and training costs. The value of the first part of the objective function may be seen as a measure of inflexibility. This conforms with the flexibility measure developed by Jordan and Graves (1995). Their (in)flexibility measure may be interpreted as the probability of having workers who are fully loaded while simultaneously having underutilized workers. If the workload is balanced in all situations the inflexibility is zero, according to Jordan and Graves (1995), and the value of the first part of our objective function is minimal. In our model, the value of the first part of the objective function is also determined by the efficiency of the workers. The more that workers are deployed at their most efficient task, the better the flexibility will be, i.e., the lower the value of the first term of the objective function. The inclusion of efficiency considerations may be seen as an extension of the work of Jordan and Graves (1995).

Constraint (1) in the IP model forces the demand for the various machines to be assigned to the workers in all situations (k,l) . Constraint (2) forces all operators to be equally or less loaded than the bottleneck worker. The workload of a worker depends on the normalized times assigned to that worker and his efficiency at performing the tasks. Constraint (3) forces workers to be or become trained for the machines that they have to operate. Constraints (4) and (5) concern the desired minimum and maximum redundancy of each task. Constraints (6) and (7) concern the boundaries of the multifunctionality of each worker. Constraint (8) forces no work to be assigned to absent workers. Constraints (9) and (10) show the domains of variables x_{ijkl} and y_{ij} .

5. An illustrative example

This section presents a small example to illustrate the various elements and features of the model. The example concerns a small manufacturing cell consisting of 4 workers and 5 machines. Workers I, II, and III are the fixed staff in the cell. Worker IV is only assigned to the cell in periods of high demand. The periods of low and high demand may follow a seasonal pattern. We assume that both periods involve 6 months. The demand mix is different in each period. Table 1 provides information about the estimated demand in terms of machine utilization for each period. Table 1 also provides information about the current cross-training level of the operators, and the training costs involved in learning how to operate a machine. As can be seen, no training costs are involved for workers who are already qualified for operating a particular machine. In this illustrative example, we have also included some of the costs for maintenance of skills for a particular machine (MC_{ij}). We assume here that these costs are needed to keep qualifications at a certain level. In practice, these costs occur after modifications to machines or changes to the products to be produced. As will be seen, the inclusion of these costs only necessitates a small change in the IP model, indicating some adaptability of the model to real situations. Table 1 also provides information about the efficiency that a worker can realize at a particular machine and the desired payback period for cross-training effort. As mentioned before, the variety of efficiency levels at a particular machine depends on the labor intensity of the tasks involved. The cross-training payback period depends on machine as well as worker characteristics, as described in section 4.

The information provided in table 1 may be regarded as the starting situation for the management of the firm for developing a cross-training program. We assume that a basic objective of the management is that the team of workers has to be able to answer the demand, in both demand situations, without additional help. The total annual working time of a worker is assumed to be 1650 hours. This means that the total workload of the bottleneck worker for each period should be less than $1650/2$. It is easy to check that this will be the case if the workload is balanced over the operators who are present, assuming an efficiency factor of 1. In both periods, the workers are then loaded for 701.25 hours (= 85% utilization x $1650/2$). Achieving a balanced workload, however, requires some cross-training. In the current situation (see table 1), for instance, operator II will be the bottleneck in the high demand period and a balanced workload is not possible. The workload of operator II in the high demand period, expressed in required labor utilization, will be 152% (= $1.0 \times 80 + 0.9 \times 80$) since he is the only employee who is able to operate machines 2 and 5. We assume an average rate (c_{kl}) of EUR 50 per bottleneck hour. These costs are linear to the load of the bottleneck worker. Labor and machine costs, fixed in the firm in our case study, are not included in the rate. Depending on the situation (k, l), other rate values can be considered. In the first instance, however, we assume the average rate for both situations. We also assume that the management of the firm has not set boundaries on the levels of multifunctionality and redundancy.

Table 1 Starting situation for developing a cross-training program.

	Mach. 1	Mach. 2	Mach. 3	Mach. 4	Mach. 5
$D_{i,high}$ [*]	70%	80%	60%	50%	80%
$D_{i,low}$ ^{**}	55%	30%	50%	80%	40%
Operator I					
Cross-training situation ^{***}	X	-	-	X	-
Training costs ^{****}	0	5000	7500	0	10000
Maintenance costs ^{*****}	1000	750	500	1000	750
Efficiency factor (e_{i1})	0.8	1.0	0.6	0.9	0.8
Cross-training payback period ($1/c_{i1}$)	2	2	1	2	2
Operator II					
Cross-training situation ^{***}	-	X	-	-	X
Training costs ^{****}	10000	0	7500	7500	0
Maintenance costs ^{*****}	1000	750	500	1000	750
Efficiency factor (e_{i2})	0.9	1.0	0.8	1.0	0.9
Cross-training payback period ($1/c_{i2}$)	2	4	1	3	2
Operator III					
Cross-training situation ^{***}	-	-	X	X	-
Training costs ^{****}	10000	5000	0	0	10000
Maintenance costs ^{*****}	1000	750	500	1000	750
Efficiency factor (e_{i3})	1.1	1.0	1.2	1.0	1.1
Cross-training payback period ($1/c_{i3}$)	2	3	1	3	2
Operator IV					
Cross-training situation ^{***}	-	-	X	X	-
Training costs ^{****}	10000	5000	0	0	10000
Maintenance costs ^{*****}	1000	750	500	1000	750
Efficiency factor (e_{i4})	1.4	1.0	1.8	1.2	1.4
Cross-training payback period ($1/c_{i4}$)	1	1	1	1	1

(*) $D_{i,high}$ is the demand expressed by average machine utilization, assuming an efficiency of 1, in the 6-month period of high demand. It has to be multiplied by 1650/2 in order to get the demand in normalized hours.

(**) $D_{i,low}$ is the demand expressed by average machine utilization, assuming an efficiency of 1, in the 6-month period of low demand. It has to be multiplied by 1650/2 in order to get the demand in normalized hours.

(***) – means that the operator is not able to operate a particular machine; X means that the operator is trained for the machine.

(****) Training costs, TC_{ij} , in EUR

(*****) Maintenance costs, MC_{ij} , in EUR

Given the above information, the IP model for this particular case can be filled in. There are basically two situations (k,l) that need to be considered in the model: the high and low demand periods, or the 4 and 3 workers' periods. We have denoted these situations as A and B respectively. The model can now be described as follows:

$$\text{Minimize } \pi_1(50 WB_A + 50 WB_B) + \pi_2 \sum_i \sum_j (c_{ij} TC_{ij} + MC_{ij}) y_{ij}$$

subject to:

$$D_{iA} - \sum_j x_{ijA} \leq 0 \quad \forall i$$

$$D_{iB} - \sum_j x_{ijB} \leq 0 \quad \forall i$$

$$\sum_i e_{ij} x_{ijA} \leq WB_A \quad \forall j$$

$$\sum_i e_{ij} x_{ijB} \leq WB_B \quad \forall j$$

$$x_{ijA} \leq \Omega y_{ij} \quad \forall i, j$$

$$x_{ijB} \leq \Omega y_{ij} \quad \forall i, j$$

$$x_{i4B} = 0$$

$$x_{ijA} \text{ and } x_{ijB} \geq 0 \quad \forall i, j, k$$

$$y_{ij} = 0 \text{ or } 1 \quad \forall i, j$$

The first term of the objective function, $(50 WB_A + 50 WB_B)$, concerns the annual operating costs. The second term, $\sum_i \sum_j (c_{ij} TC_{ij} + MC_{ij}) y_{ij}$, concerns the annual training plus maintenance costs. The constraints are more or less similar to the ones presented in the general model in section 4. We used LINGO 5.0 to solve the above model, using the data in Table 1. It took only a few seconds to solve the problem, using a MMX Pentium 200 MHz with 64 MB RAM.

Table 2 shows the distribution of required skills in order to get an optimal result (with $\pi_1=1$ and $\pi_2=1$). As can be seen, workers II and III need additional cross-training for machines 4 and 2, respectively. The qualifications of workers III and IV for machine 4 are superfluous and some maintenance costs can be saved by not assigning these workers to this machine. Table 2 also shows that the workload can be evenly distributed among the present workers in both situations. This indicates the presence of effective chains (worker qualifications) through which work can be shifted from heavily loaded workers to less loaded workers. As can be seen, some machines (1 and 5) are only chained to one worker, indicating the risk of a bottleneck worker (or: subgroup of one worker) in the event of a very high demand for machines 1 and 5. However, the given demand situations exclude this risk. In this particular situation, therefore, a complete chaining of workers and machines is not needed to realize an optimal situation.

Table 2 Qualifications needed or superfluous in the case situation

Machine\Worker	I	II	III	IV
1	X			
2		X	A	
3			X	X
4	X	A	O	O
5		X		
workload situation A	734.25	734.25	734.25	734.25
workload situation B	675.91	675.91	675.91	0

X means that the qualification is needed and that the operator was already trained for the machine; A means that the qualification is needed and that cross-training of the worker is required; O means that the operator is qualified to operate the machine but that this qualification is not required.

In the situation in table 2, the workload of all workers is higher in demand situation A (the high demand situation) than in demand situation B, which means that the slack in period A, available for coping with job interaction, is less and a more effective scheduling of jobs is needed. The slack in period A equals $825-734.25=90.75$ hours. A more evenly distributed workload among both periods can be realized by increasing the hourly rate for period A,

relative to the hourly rate for period B, in the IP model. This relative increase is reasonable if the hourly rate also includes the costs of coordination and scheduling. The annual training plus maintenance costs in the situation in table 2 (i.e. $\pi_1/\pi_2=1$) are EUR 4,167. Figure 2 depicts the costs in various (π_1/π_2) situations. If the management of the firm is concerned about the limited amount of slack in the situation in table 2, then they may consider more cross-training effort. In terms of the model, a higher value for π_1 can be chosen. Table 3 shows the cross-training result should $\pi_1=10$ and $\pi_2=1$. As can be seen, this situation requires five additional qualifications and five existing qualifications are superfluous. The annual training plus maintenance costs in this situation are EUR 21,667.

A major objective of management may be to minimize total costs. Figure 2 illustrates the total costs for various π_1/π_2 ratios. There is a relatively broad range of π_1/π_2 ratios (between 1/2 and 1/8) which lead to an optimal cost result. This indicates the robustness of the model solution. Between the π_1/π_2 values of 1/2 to 1/8, the cross-training situation is equal. Table 4 depicts this cross-training situation. The relatively low training + maintenance costs in this situation has the drawback that the workload of the bottleneck worker is relatively high and the workload is not balanced in situation B. As mentioned earlier, an unbalanced workload indicates the presence of heavily loaded workers who cannot be released by shifting work to less loaded workers. In this particular case, the load of workers I and III, in workload situation B, cannot be shifted to worker II. All the work for machine 2 in workload situation B is already assigned to worker II and cannot be further used as a chain to release the other workers. This shows the limited capacity of a chain (or qualification). As mentioned before, a relatively high load on the bottleneck worker will be likely to have a negative effect on the performance of the manufacturing cell. Unbalance may also give rise to feelings of inequity in a team.

Table 3 Qualifications needed or superfluous in the case situation ($\pi_1=10, \pi_2=1$)

Machine\Worker	I	II	III	IV
1	X		A	
2		O	A	A
3	A		O	O
4	O	A	X	O
5		X		
workload situation A	619.46	619.46	619.46	619.46
workload situation B	605.61	605.61	605.61	0

X means that the qualification is needed and that the operator was already trained for the machine; A means that the qualification is needed and that cross-training of the worker is required; O means that the operator is qualified to operate the machine but that this qualification is not required.

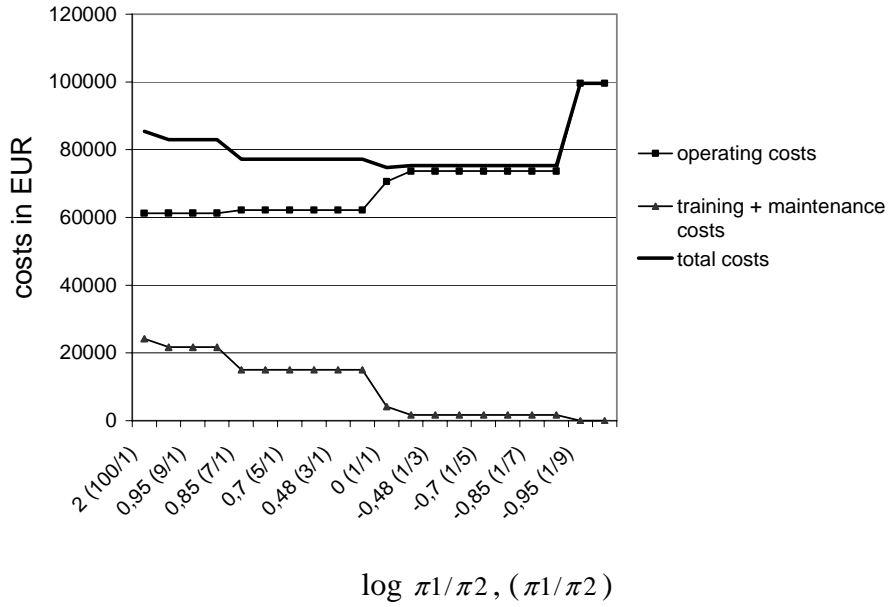


Fig. 2 Total costs as a function of the ratio (π_1/π_2)

Table 4 Qualifications needed or superfluous in the case situation ($\pi_1=1, \pi_2=2, \dots, 8$)

Machine\Worker	I	II	III	IV
1	X			
2		X	A	
3			X	X
4	X		X	O
5		X		
workload situation A	734.25	734.25	734.25	734.25
workload situation B	738.18	544.50	738.18	0

X means that the qualification is needed and that the operator was already trained for the machine; A means that the qualification is needed and that cross-training of the worker is required; O means that the operator is qualified to operate the machine but that this qualification is not required.

The example in this section distinguishes only two demand/supply situations. A practical case probably contains many situations. The demand for and the presence of workers may be different for each day or week. We think that it is sufficient to integrate only the major demand/supply situations that differ significantly from each other in the model. It is likely that the resulting ideal cross-training situation will satisfy the needs in many other scenarios. This assumption is based on the “chaining” situation gained after running the model (see section 3). The major chains in the cross-training situation are likely to absorb the variations in minor demand/supply situations. Further, the outcome of the model may be regarded as a starting point for the developer of a cross-training program. The manager may decide to add cross-training based on his knowledge of the presence of specific situations.

6. Conclusions

This study has shown that cross-training decisions in a cellular manufacturing environment should support the forming of effective “chains” between workers and machines through which work can be shifted, directly or indirectly, from a heavily loaded worker to a less loaded worker. By doing so, a balanced workload situation can be realized that has a positive effect on operational performance and, probably, also on the social climate within a team of workers. Based on this insight, we have developed an IP model to support decision-making with respect to cross-training in a manufacturing cell. The model is helpful when making a trade-off between training costs and the workload balance among workers in a manufacturing cell. The workload balance indicates the usefulness of labor flexibility in a particular situation.

The example given in section 5 is purely illustrative, designed to show the various elements and features of the model. The example problem was solved in a few seconds on a personal computer. With the recent rapid growth in computing power, larger mathematical programming problems are also becoming solvable within acceptable time limits. Further, in larger problem contexts, several pragmatic factors can be utilized to limit the solution space. These factors include the exclusion of simple work that can be performed by temporary workers if need be, and the limitation of the demand and labor situations to only the extreme ones.

The example in section 5 provides some important insights into the complexity of “chaining”. First, a complete chaining of all workers and machines (i.e. one chain of qualifications links all workers and machines) may not be needed to realize an optimal result. This depends on the various demand situations incorporated in the study. Second, each chain has a limited capacity and may not be able to release a bottleneck worker completely in order to get a balanced situation. The capacity of the chain equals the demand for the particular machine. These complexities of “chaining” stress the need for an analytical model to solve the cross-training problem.

We realize that several aspects encountered in practice have not been included in our study. Issues such as power and personal interests are not dealt with by our study either. We also realize that the number of variables taken into account in our study is limited. We assumed, for example, that training cannot be applied to increase the efficiency of a worker at a particular machine. We also assumed that workers are not able to deal with two or more machines simultaneously. These assumptions may not be true in many situations. Further, in reality there may be some overlap in training needs for the various tasks that suggest a logical sequence in a training program for a worker. This will have an impact on the total

training costs. All of these elements deserve to be incorporated into future investigations (see also Pennathur *et al.* 1999). The study presented in this paper should be regarded as an initial probe to determine an optimal cross-training situation for a team of workers.

Another major issue that requires further investigation concerns our belief that the load on the bottleneck worker is an important indicator of the operational performance of a team. As made clear in the example in figure 1, a low workload for the bottleneck worker indicates a balanced workload situation in which there are useful “chains” through which work can be transferred from heavily loaded workers to less loaded workers. Further, a low workload for the bottleneck worker is important for creating the necessary slack to deal with job interaction in real situations (see e.g. Raaymakers and Fransoo, 2000). It would be interesting to study which circumstances and to what extent a low workload on the bottleneck worker supports the operational performance of a manufacturing cell, such as short throughput times of jobs and a high delivery performance of jobs.

References

- Askin, R.G. and Huang, Y., 2001, Forming effective worker teams for cellular manufacturing. *International Journal of Production Research*, 39(11), 2431-2451.
- Austin, W, 1977, Equity theory and social comparison processes. In Suls, J.M. and Miller, R.L. (Eds.), *Social Comparison Processes: Theoretical and Empirical Perspectives*, Hemisphere, Washington, DC.
- Bobrowski P.M and Park P.S., 1993, An evaluation of labor assignment rules when workers are not perfectly interchangeable. *Journal of Operations Management*, 11, 257-268.
- Brusco, M.J. and Johns, T.R., 1998, Staffing a multiskilled workforce with varying levels of productivity: An analysis of cross-training policies. *Decision Sciences*, 29, 499-515.
- Brusco, M.J., Johns, T.R., and Reed, J.H., 1998, Cross-utilization of a two-skilled workforce. *International Journal of Operations & Production Management*, 18(6), 555-564.
- Carnall, C.A., 1982, Semi-autonomous work groups and the social structure of the organization. *Journal of Management Studies*, 19, 277-294.
- Clark, J., 1993, Full flexibility and self-supervision in an automated factory. In J. Clark (Ed.), *Human Resource Management and technical change* (Broughton Gifford: Cornwell Press Ltd), pp.116-136.
- Cordery, J., Sevaston, P., Mueller, W., and Parker, S., 1993, Correlates of employee attitudes toward functional flexibility. *Human Relations*, 46, 705-723.
- Fazakerley, G.M., 1976, A research report on the human aspects of group technology and cellular manufacture. *International Journal of Production Research*, 14, 123-134.
- Fry, T.D., Kher, H.V., and Malhotra, M.K., 1995, Managing worker flexibility and attrition in dual resource constrained job shops. *International Journal of Production Research*, 33, 2136-2179.
- Hut, J.A. and Molleman, E., 1998, Empowerment and team development. *Team Performance Management Journal*, 4, 53-66.

Jackson, S.E., 1996, The consequences of diversity in multidisciplinary work teams. In: M.A. West (Ed.), *Handbook of Work Group Psychology*. (New York: John Wiley and Sons Ltd).

Jordan, W.C. and Graves, S.C., 1995, Principles on the benefits of manufacturing process flexibility. *Management Science*, 41, 577-594.

Kher, H.V. and Malhotra, M.K., 1994, Acquiring and Operationalizing Worker Flexibility in Dual Resource Constrained Job Shops with Worker Transfer Delays and Learning Losses. *Omega*, 22, 521-533.

Lau, D.C. and Murnighan, J.K., 1998, Demographic diversity and faultlines: the compositional dynamics of organizational groups. *The Academy of Management Review*, 23, 325-340.

Min, H. and Shin, D., 1993, Simultaneous formation of machine and human cells in group technology: a multiple objective approach. *International Journal of Production Research*, 31(10), 2307-2318.

Molleman, E. and Slomp, J., 1999, Functional Flexibility and Team Performance. *International Journal of Production Research*, 37, 1837-1858.

Molleman, E., Slomp, J., and Rolefes, S., 2002, The Evolution of a Cellular Manufacturing System - A longitudinal case study. *International Journal of Production Economics*, 75, 305-322.

Norman, B.A., Tharmmaphornphilas, W., Needy, K.L., Bidanda, B., and Warner, R.C., 2002, Worker assignment in cellular manufacturing considering technical and human skills. *International Journal of Production Research*, 40(6), 1479-1492.

Park, P.S. and Bobrowski, P.M., 1989, Job Release and Labor Flexibility in a Dual Resource Constrained Job Shop. *Journal of Operations Management*, 8, 230-249.

Pennathur, A., Mital, A., Rajan, V., Kaber, D., Ray, P., Huston, R., Thompson, D., Markle, G., Pitman, M.A., Bishu, R., Crumpton, L., Deivanayagam, S., Fernandez, J., McElwee, M., McMulkin, M., and Sule, D., 1999, A Framework for training workers in contemporary manufacturing environments. *Int. J. Computer Integrated Manufacturing*, 12(4), 291-310.

Raaymakers, W.H.M. and Fransoo, J.C., 2000, Identification of aggregate resource and job set characteristics for predicting job set makespan in batch process industries. *Int. J. Production Economics*, 68, 137-149.

Stewart, B.D., Webster, D.B., Ahmad, S., and Matson, J.O., 1994, Mathematical models for developing a flexible workforce. *International Journal of Production Economics*, 36, 243-254.

Süer, G.A., 1996, Optimal operator assignment and cell loading in labor-intensive manufacturing cells. *Computers and Industrial Engineering*, 26(4), 155-159.

Suresh, N.C. and Slomp J., 2001, Labor Assignment and Grouping in Cellular Manufacturing – a Multi-Objective Methodology. *International Journal of Production Research*, 39(18), 4103-4131.

Treleven, M., 1989, A review of dual resource constrained systems research. *IIE Transactions*, 21, 279-287.

CROSS-TRAINING

Van den Beukel, A.L. and Molleman, E., 1998, Multifunctionality: The driving and constraining forces. *Human Factors and Ergonomics in Manufacturing*, 8, 303-321.

Wilke, H.A.M. and Meertens, R.W., 1994, *Group performance* (London: Routledge).

DEVELOPMENT AND EVALUATION OF CROSS-TRAINING
POLICIES FOR MANUFACTURING TEAMS⁴

Jos A.C. Bokhorst, Jannes Slomp and Eric Molleman

ABSTRACT

This study addresses the problem of developing and evaluating cross-training policies for manufacturing teams from a human resource management (HRM) and operations management (OM) viewpoint. A cross-training policy can be regarded as a set of rules to determine the distribution of workers' skills. The specific way in which workers and machines are connected determines the agility of the workforce. In this article, we develop an Integer Goal Programming (IGP) model to support a consequent application of alternative cross-training policies. A simulation study is performed to assess the performance of the resulting cross-training configurations within three routing structures: a parallel structure, a serial structure, and a job shop structure. Results indicate that within all routing structures, the focus of cross-training policies depends on whether a HRM or an OM viewpoint is considered. Within the parallel and the serial structures, however, HRM and OM goals are compatible and can be integrated within a single cross-training policy. Within the job shop structure, the integration of both OM and HRM goals within one cross-training policy is more difficult.

1. Introduction

A manufacturing team can be defined as a group of workers responsible for manufacturing a family of various part-types. The team makes use of a set of different machines required to manufacture the various part-types. Each part-type must visit one or more machines according to its routing structure. In many manufacturing systems, the number of machines is larger than the number of workers in a team. Such systems are known as "Dual Resource Constrained" (hereafter, DRC) systems, referring to the need for both workers and machines (see, e.g., Treleven, 1989). Labor flexibility is a major research topic related to DRC systems. Cross-training, which is a particular specification of labor flexibility, concerns the training of multiple workers for certain tasks or machines. This paper is devoted to the question of which workers should be trained for which machines. In more general terms, it asks, "What is an effective cross-training policy?" This is an important question, since the specific way in which workers and machines are connected determines the agility of the workforce with respect to changes in the demand for and the supply of labor. In order to answer this question, we must first consider which aspects are important in developing a cross-training policy. Second, once alternative cross-training policies have been developed, the effectiveness of the various cross-training configurations resulting from the application of these policies should be evaluated. Figure 1 presents an overview of the theoretical model upon which this paper is based.

⁴ This paper is published in IIE Transactions, Vol. 36(10), 969-984, 2004.

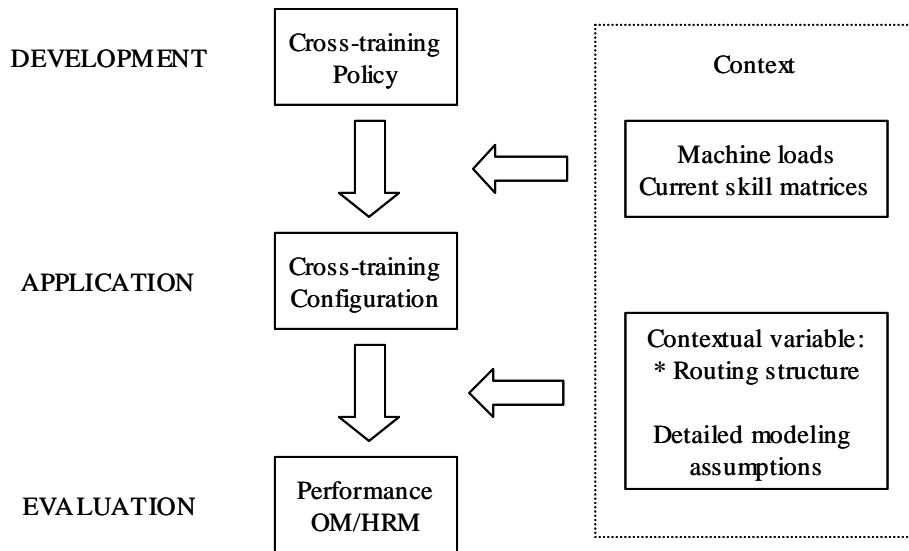


Figure 1. Development, application, and evaluation of cross-training policies.

A cross-training policy can be regarded as a set of rules for determining the distribution of workers' skills. These rules specify what decisions are made concerning aspects that are considered important in the development of a cross-training policy. Developing cross-training policies thus involves deciding which aspects are important to include, and also defining decision rules to specify how these aspects will be addressed. Applying a cross-training policy to a manufacturing team results in a skill matrix indicating which workers should be cross-trained for which machine. We call this resulting skill matrix a "cross-training configuration." In this paper, we use simple aggregated data from a generic manufacturing team applying cross-training policies to create cross-training configurations. We use information concerning the workloads of various machines and the current skill matrix of workers as a starting point. To evaluate alternative cross-training policies, we use simulation to study the performance of the resulting cross-training configurations in more detail. Our focus is on minimizing mean flow time from an Operations Management (OM) viewpoint, and on minimizing the standard deviation of the distribution of workload among workers (SDworkload) from a human resource management (HRM) viewpoint. More detailed contextual information, including details on the routing of jobs and other modeling assumptions, is required for the simulation. Routing structure is studied as a contextual variable.

Section 2 deals with the theoretical model by first discussing important aspects to consider in the development of a cross-training policy. Following a review of the cross-training literature, we define eight alternative cross-training policies based on different choices with respect to these aspects. To support a consequent application of these cross-training policies, we develop an Integer Goal Programming (IGP) model. Finally, we present the eight resulting cross-training configurations and discuss routing structure as a contextual variable. Section 3 describes the design of a simulation study comparing the performance of the eight cross-training configurations, the results of which are presented in Section 4. Section 5 gives the conclusions of our study, indicates the practical relevance of the outcomes, and suggests topics for further research.

2. Theoretical model

2.1. Development of cross-training policies

The following are five important aspects to consider when developing a cross-training policy: the extent of cross-training, the concept of “chaining”, multi-functionality, machine coverage, and collective responsibility. These aspects will be discussed consecutively, followed by a description of eight alternative cross-training policies based on different choices concerning these aspects.

2.1.1. Extent of cross-training

By the extent of cross-training, we mean the number of (additional) cross-trainings that are needed in the manufacturing team. Although increases in cross-training can positively affect system performance, several papers have shown a diminishing positive effect of a stepwise increase of the level of labor flexibility (Park and Bobrowski, 1989; Malhotra *et al.*, 1993; Fry *et al.*, 1995; Campbell, 1999; Molleman and Slomp, 1999). Most of the positive effects can be achieved without going to the extreme of total flexibility. Total flexibility requires training of all workers for all machines, which can be costly. Further, Kher and Malhotra (1994) showed that higher levels of labor flexibility lead to more labor transfers, resulting in considerable losses in productivity. This productivity loss results from, among other factors, the time required for orientation at new work stations, to access information about the job to be performed at the new machine and to (re-)learn the setup procedures. The risk of productivity losses due to increased worker transfers is an argument for limiting labor flexibility.

The above arguments against full flexibility in a manufacturing cell raise questions concerning the extent to which the labor force should be cross-trained and, more precisely, of which workers should be cross-trained for which machines. Until these questions are addressed, research within the field of labor flexibility cannot progress (see Treleven, 1989; Pennathur *et al.*, 1999).

2.1.2. Chaining

Jordan and Graves (1995) stressed the importance of chaining in the case of limited flexibility. They studied the effect of process flexibility, which they define as the ability of plants to produce different types of products. This type of flexibility is conceptually equivalent to labor flexibility, which refers to the ability of workers to operate different machines. Brusco and Johns (1998) recognized this and used the term “chaining” to explain the preference of some of their cross-training patterns. They presented a linear programming model that minimizes costs associated with workforce staffing, subject to the satisfaction of minimum labor requirements across a planning horizon. They used their model to evaluate eight cross-training structures across various patterns of labor requirements, reaching the important conclusion that “chaining of employee skill classes across work activity categories” is a basic element of successful cross-training structures.

Hopp *et al.* (2002) studied two cross-training strategies for serial production systems with flexible servers. They stated that the two primary benefits of workforce agility in this environment are “capacity balancing,” which is needed if lines are unbalanced with respect to the average workload of each station, and “variability buffering,” which provides a solution for worker idleness caused by variability in processing times. The number of workers is equal to the number of stations, but it is possible for more than one worker to

work at a given station. Assuming that each station is attended initially by one worker, the “cherry picking” strategy adds a minimum number of additional skills in such a way that workers with excess capacity are assigned to one or more stations that require help in order to balance the line. In this way, underutilized workers can directly help over-utilized stations. In contrast, the “D-skill chaining” strategy enables workers to help over-utilized stations indirectly by means of paths through other workers. Under the D-skill chaining strategy, each worker is cross-trained for an initial station and for the next D-1 stations in the line. Hopp *et al.* (2002) showed that the 2-skill chaining strategy is potentially robust and efficient in obtaining workforce agility in serial production lines.

Chaining provides the ability to shift work from a worker with a heavy workload to a worker with a lighter workload, leading – directly or indirectly – to a more balanced workload. Chaining therefore supports the efficient use of labor capacity and provides sufficient agility to respond to changes in demand, thus enabling fluctuations in the mix of work to be absorbed. Chaining also reduces the likelihood that subgroups may emerge and cause inter-group conflicts, leading to the disintegration of a team (see Wilke and Meertens, 1994). Chaining is therefore an important aspect to include in developing cross-training policies.

2.1.3. Multi-functionality

A worker’s multi-functionality refers to the number of machines that can be operated by that worker. Demand variation and worker absenteeism are important conditions affecting the required level of labor flexibility. In a study concerning the effects of labor flexibility on team performance, Molleman and Slomp (1999) presented a mathematical model for assigning multi-skilled workers to the various tasks (or machines) in a team. Team performance was measured as the shortage of labor capacity, the minimum time needed to perform all tasks (the workload of the bottleneck worker), and the cumulative time needed to perform all tasks. An application of this model showed that a uniform distribution of worker multi-functionality provided the best team performance under conditions of absenteeism with little or no fluctuation in demand. They indicated that absenteeism should be considered a major reason for investing in labor flexibility. Assuming uniform absenteeism among workers, this can be explained by the fact that the absenteeism of highly multi-functional workers causes the performance of a team to deteriorate much more than does the absenteeism of less multi-functional workers. An equal distribution of worker skills is also better from a social viewpoint, since feelings of interpersonal justice and equity are enhanced when workers in a team help each other and share their workloads (see for example Austin, 1977).

Most prior studies on DRC systems focus on single-level labor flexibility, in which workers receive the same degree of cross-training and are thus equal in terms of multi-functionality. Little is known about the effects of unequal multi-functionality. One exception is a study by Felan and Fry (2001), who focus on multi-level flexibility, where workers are trained to work in a different number of departments. They found that cross-training configurations with unequal levels of cross-training lead to better flow times. Because labor learning was included as a factor in the model, their results may be explained by the fact that workers with few skills are able to maximize the task proficiency of those skills, while the few workers with many skills are able to respond to temporary overloads. Felan and Fry (2001) did not consider absenteeism. As a result, the relative benefits of choosing to pursue either equal or unequal multi-functionality remain unclear. In a situation with absenteeism and without labor learning, however, we expect equal multi-functionality to be the best option.

2.1.4. Machine coverage

Machine coverage is defined as the number of workers who are able to operate a machine. Molleman and Slomp (1999) suggested that, as a general training policy, each task should be mastered by at least two workers in order to reduce the negative impact of absenteeism. Above this minimal level of flexibility, the demand of work should dictate training decisions. For example, workers should be trained for the task with the highest demand.

Whether the level of coverage should be as equal as possible for all machines or if some differentiation should be allowed remains an open question. If many workers are able to perform a particular operation, it is likely that some workers will never operate the machine in question. Equal machine coverage is therefore likely to minimize the number of unnecessary worker skills. On the other hand, equalizing machine coverage neglects differences in the utilization of machines. A relatively high level of machine coverage for heavily utilized machines may reduce unnecessary idle time due to lack of workers having the necessary skills to operate those machines. Additionally, the unequal division of machine coverage takes the variety of machines in a team into account. Because the required level of learning effort is likely to vary among machines, higher coverage may be more efficient for machines for which workers can be easily trained. Although the question of equalizing or differentiating machine coverage is worthwhile to address when developing cross-training policies, prior studies have not, to the best of our knowledge, paid much attention to this question.

2.1.5. Collective responsibility

Collective responsibility refers to the distribution of responsibilities within a team. Social comparison theory (as discussed by Jellison and Arkin, 1977, for example) argues that team members prefer complementarity in skill distribution, because they expect this to enhance both their own identity and the performance of the group as a whole. Being a specialist enhances an individual's sense of uniqueness and irreplaceability and draws attention to a worker's contribution to group performance (Clark, 1993). Cross-training may therefore inhibit motivation (Fazakerley, 1976). Furthermore, studies pertaining to diversity show that creativity and motivation are more prevalent in teams whose members have different – but somewhat overlapping – skills (for example, see Jackson, 1996). Ashkenas *et al.* (1995) argue that cross-training can diminish job boundaries. When more workers are responsible for the same task, the situation may arise in which none of them feels exclusively responsible for that task. This phenomenon is known as social loafing (see Latané, Williams and Harkins, 1979; Wilke and Meertens, 1994).

In its turn, social loafing may give rise to feelings of inequity and lead to conflicts (Kerr and Bruun, 1983). When cross-training workers, therefore, there are reasons to minimize the overlap of responsibilities. Additional cross-trainings should thus focus on machines for which the workload is as low as possible. The total workload of the machines to which a worker can be assigned can be regarded as a measure of that worker's responsibility, which may be (partly) shared by other workers who can also be assigned to one or more of these machines.

Responsibility for an equal amount of a (partially) shared workload supports equity among workers. We define collective responsibility as the sum of all worker responsibilities minus the total workload of the machines. In other words, collective responsibility measures the sum of all overlapping responsibilities. Minimizing collective responsibility leads to a

situation where workers are most unique and give a specialized contribution to the performance of a team.

On the other hand, policies that minimize the overlap of responsibilities may also minimize the workload that can be assigned to individual workers and thereby the assignment possibilities during working hours. This may lead to situations in which some workers are idle, even as some machines wait for qualified workers. Such a situation is likely to have negative consequences for the flow times of jobs. Moreover, when one or more workers are idle, feelings of inequity may develop among team members. As more responsibilities are shared, more opportunities arise for workers to help each other and to equalize workloads. The foregoing points out that the decision of minimizing or maximizing collective responsibility comprises another non-obvious choice for managers in developing a cross-training policy.

2.1.6. Alternative cross-training policies

A cross-training policy can be regarded as a set of rules to specify which decisions are made with respect to the aforementioned aspects in order to determine how the skills of workers should be distributed. As we have seen, research has failed to provide unambiguous rules for addressing multi-functionality, machine coverage, and collective responsibility. In our experience, managers recognize the need for more insight into the effects of alternative cross-training policies in order to create an agile workforce able to respond efficiently and effectively to unplanned changes. We therefore consider eight alternative cross-training policies, based on two different choices that can be made with respect to each of the following aspects: multi-functionality, machine coverage, and collective responsibility (see Table 1). Within each of these cross-training policies, the same rules are included to deal with the other aspects discussed in this subsection. Further discussion follows.

Table 1. Alternative cross-training policies

Choices	Cross-training policies							
	I	II	III	IV	V	VI	VII	VIII
equal multi-functionality	NO	NO	YES	YES	NO	NO	YES	YES
equal machine coverage	YES	YES	NO	NO	NO	NO	YES	YES
collective responsibility	MIN	MAX	MIN	MAX	MIN	MAX	MIN	MAX

2.2. Application of cross-training policies

The Integer Goal Programming model presented here formalizes the various rules for specifying how important aspects should be addressed, and can subsequently be used to support the application of a cross-training policy. In the IGP model, rules are expressed in terms of goals and constraints. Each cross-training policy requires small alterations in either the goals or constraints (or both) of the IGP model. Further, we present eight cross-training configurations derived from an application of the eight cross-training policies defined in the previous subsection, using the IGP model with aggregated data from a generic manufacturing team.

2.2.1. An Integer Goal Programming model

Table 2 summarizes the important aspects to be considered in the development of a cross-training policy and shows which goals and constraints in the IGP model address these aspects.

Table 2. Important aspects to consider when developing a cross-training policy and the goals and constraints by which these aspects are expressed in the Integer Goal Programming model.

Aspect	Description (and alternative rules with aspects 3, 4 and 5)	Expression in the IGP model
1	Chaining Enable an equal workload division among the workers to encourage “chaining”.	Constraint (3)
2	Extent of cross-training Minimize the number of additional cross-trainings.	First goal in the objective function; setting <i>AddCT</i> to zero in constraint (7)
3	Multi-functionality Rule 1: equal multi-functionality per worker Rule 2: unequal multi-functionality per worker	Second goal in the objective function; constraint (8) supports the realization of an equal distribution. An unequal distribution can probably be realized by neglecting the second goal and constraint (8). An alternative we use is to give one or more operators more skills than average, before applying the model.
4	Machine coverage Rule 1: equal machine coverage Rule 2: unequal machine coverage	Third goal in the objective function; constraint (9) supports the realization of an equal distribution. We realize an unequal distribution by neglecting the third goal and constraint (9). An alternative is to cross-train a higher-than-average number of workers for particular machines.
5	Collective responsibility Rule 1: minimize collective responsibility Rule 2: maximize collective responsibility	Fourth goal in the objective function; constraint (10) supports the minimization of collective responsibility. We maximize collective responsibility (or the ease of worker assignment) by giving Φ_4 a negative value.
6	Equal worker responsibility Responsibility for an equal amount of (partly) shared workload will support the equity of workers.	Fifth goal in the objective function; constraint (11) supports the realization of an equal worker responsibility

Notation:

Index sets:

- $\{i=1, \dots, I\}$ = Index set of machines
 $\{j=1, \dots, J\}$ = Index set of workers

Parameters:

- L_i = Workload of machine i , expressed as the percentage of time that the machine will be occupied.
 WL = Workload limit of the workers (the workload that needs to be assigned to a worker)
 $MinMF$ = Minimal multi-functionality
 $MinMC$ = Minimal machine coverage
 $AddCT$ = Goal with respect to the number of additional cross-trainings
 Tr_{ij} = 0, if worker j is already trained for machine i , 1 if not
 M = Constant (large value)

Variables:

- X_{ij} = Time assigned to worker j to operate machine i
 Y_{ij} = 1, if worker j needs to be qualified for machine i ; 0, if not

Minimize

$$\Phi_1 d_{training}^+ + \Phi_2 d_{equalMF}^+ + \Phi_3 d_{equalMC}^+ + \Phi_4 d_{CR}^+ + \Phi_5 d_{WR}^+ \quad (1)$$

subject to:

$$\sum_j X_{ij} \geq L_i \quad \forall i \quad (2)$$

$$\sum_i X_{ij} \leq WL \quad \left[WL = \sum_i L_i / J \right] \quad \forall j \quad (3)$$

$$X_{ij} \leq M Y_{ij} \quad \forall i, j \quad (4)$$

$$\sum_i Y_{ij} \geq MinMF \quad \forall j \quad (5)$$

$$\sum_j Y_{ij} \geq MinMC \quad \forall i \quad (6)$$

$$\sum_i \sum_j Y_{ij} Tr_{ij} - d_{training}^+ = AddCT \quad (7)$$

$$\sum_i Y_{ij} - d_{equalMF}^+ = \sum_i \sum_j Y_{ij} / J \quad \forall j \quad (8)$$

$$\sum_j Y_{ij} - d_{equalMC}^+ = \sum_i \sum_j Y_{ij} / I \quad \forall i \quad (9)$$

$$\sum_i \sum_j Y_{ij} L_i - d_{CR}^+ = \sum_i L_i \quad (10)$$

$$\sum_i Y_{ij} L_i - d_{WR}^+ = \sum_i \sum_j Y_{ij} L_i / J \quad \forall j \quad (11)$$

$$Y_{ij} = 0 \text{ or } 1 \quad \forall i, j \quad (12)$$

The objective function (1) minimizes deviation from an optimal cross-training configuration. Constraint (2) demands that all the work be assigned to the various workers. The IGP model is likely to realize a chained graph by means of constraint (3). This constraint demands a cross-training configuration in which all workers can have equal workloads. Constraint (4) forces workers to be or become trained for the machines they must operate. Constraints (5) and (6) concern the minimum levels of multi-functionality and machine coverage, respectively. These two constraints indicate basic choices facing the manager responsible for cross-training workers.

To what extent is a minimal level of multi-functionality and machine coverage needed? A certain level of multi-functionality and machine coverage is needed in order to deal with fluctuations. When there is too much multi-functionality and machine coverage, worker skills may remain unused and workers may begin to feel that their contributions to team performance are less unique.

Constraints (7) to (11) are the goal constraints and indicate other cross-training choices within manufacturing teams. The first goal of the objective function is to minimize the deviation from the desired number of additional cross-trainings ($AddCT$). A chained graph is easily obtained by fully cross-training the team. As mentioned before, however, full cross-training is not the ideal situation in many cases. Constraint (7) calculates the deviation from the desired number of additional cross-trainings ($AddCT$). In reality, however, the training budget may also be an important factor. This is easily expressed by means of constraint (7), using the following procedure: $AddCT$ and Tr_{ij} must be redefined as the training budget and the training costs of cross-training worker j for machine i , respectively. We assume that minimizing the number of additional worker skills is a major objective. In practice, managers strive to balance the positive performance effects of cross-training with the integral costs of additional worker skills.

The second goal of the objective function concerns balancing multi-functionality among workers by minimizing the maximal deviation ($d_{equalMF}^+$) from optimal multi-functionality. Constraint (8) calculates this deviation. Optimal multi-functionality is expressed as the configuration in which all workers are skilled for an equal number of machines. The third goal in the objective function minimizes the maximal deviation ($d_{equalMC}^+$) from optimal machine coverage. Constraint (9) calculates this deviation. Optimal machine coverage is expressed as the configuration in which all machines can be operated by the same number

of workers. To reduce the overlap of responsibilities, additional cross-trainings should concentrate on machines whose workloads are as low as possible.

The fourth goal in the objective function focuses on minimizing deviation (d_{CR}^+) from the optimal situation where each worker has a clear and unique responsibility, or in other words, where collective responsibility is minimized. Constraint (10) is the related goal constraint. The fifth goal of the objective function concerns the equalization of worker responsibility (defined as the sum of the workloads of the machines to which a worker can be assigned) among all workers. This goal supports equity among workers. Constraint (11) calculates the maximum deviation (d_{WR}^+) from the optimal situation in which all workers are responsible for an equal amount of the (shared) workload.

As presented here the IGP model can be seen either as a weighted or a lexicographic integer goal programming model. The weighted IGP model minimizes a weighted sum of undesirable deviations from the decision-maker's set of targets. All goals are considered simultaneously. The weights in the above model are indicated as $\Phi_1, \Phi_2, \Phi_3, \Phi_4,$ and Φ_5 . In the lexicographic IGP model, the symbols $\Phi_1, \Phi_2, \Phi_3, \Phi_4,$ and Φ_5 indicate a priority sequence among the various goals. The solution is gained by demanding that higher priority goals are first satisfied as closely as possible. Only then are lower priority goals considered. Many managerial problems have a lexicographic character. In the following section, we use a lexicographic approach to solve a cross-training problem.

2.2.2. Cross-training configurations

Using the IGP model, we formally applied the eight cross-training policies of Table 1 to a system with 5 workers and 10 machines with specific machine workloads (defined as the percentage of the time that the machine is occupied during the presence of the five workers). We began with the following assumptions: First, we assumed that none of the workers is trained initially. Further, we assumed the final number of worker skills in each configuration to be 29. In the comparison of the various configurations, a fixed number of cross-trainings ensures that performance differences cannot be attributed to differences in the number of cross-trainings per configuration.

We did not specify a minimal level of worker multi-functionality (see constraint 5). In our case situation, workers be minimally trained for two machines because of constraint (3), which demands the possibility of an equally utilized workforce. Finally, we chose a minimal machine coverage of 2 (constraint 6), in order to enable a team to perform all operations in case of absenteeism of one worker. This does not ensure coverage if two or more workers are absent, but this also occurs less often than the absence of a single worker. The average labor utilization in the system is 88% ($= \sum L_i / 5$). This percentage is in conformity with other literature on DRC systems, where labor utilization is often set at approximately 90 percent (see Treleven, 1989).

To create an unequal distribution of machine coverage, we neglected the third goal of the IGP model. To create an unequal distribution of worker skills, we fully cross-trained two workers before applying the IGP model. The eight resulting cross-training configurations are shown in Table 3.

Table 3. Eight cross-training configurations

Machine (load)	I					II				
	Worker					Worker				
	W1	W2	W3	W4	W5	W1	W2	W3	W4	W5
M1 (79.1)	1	1				1	1			1
M2 (72.8)	1	1	1			1	1		1	
M3 (64.7)	1	1			1	1	1			1
M4 (55.4)	1	1			1	1	1		1	
M5 (47.5)	1	1	1			1	1	1		
M6 (40.4)	1	1		1		1	1	1		
M7 (30.3)	1	1		1		1	1	1		
M8 (25.8)	1	1		1		1	1	1		
M9 (17.9)	1	1		1		1	1		1	
M10 (6.1)	1	1		1		1	1			

Machine (load)	III					IV				
	Worker					Worker				
	W1	W2	W3	W4	W5	W1	W2	W3	W4	W5
M1 (79.1)	1	1				1	1	1	1	1
M2 (72.8)	1			1		1	1	1	1	1
M3 (64.7)			1		1	1	1	1	1	1
M4 (55.4)				1	1		1	1		
M5 (47.5)		1	1						1	1
M6 (40.4)			1		1	1				1
M7 (30.3)		1		1		1	1			
M8 (25.8)	1	1	1	1	1			1	1	
M9 (17.9)	1	1	1	1	1	1			1	
M10 (6.1)	1	1	1	1	1		1	1		

Machine (load)	V					VI				
	Worker					Worker				
	W1	W2	W3	W4	W5	W1	W2	W3	W4	W5
M1 (79.1)	1	1				1	1	1	1	1
M2 (72.8)	1	1				1	1	1	1	1
M3 (64.7)	1	1	1			1	1	1		1
M4 (55.4)	1	1		1		1	1		1	
M5 (47.5)	1	1			1	1	1			
M6 (40.4)	1	1			1	1	1			
M7 (30.3)	1	1		1		1	1			
M8 (25.8)	1	1	1			1	1			
M9 (17.9)	1	1				1	1			
M10 (6.1)	1	1	1	1	1	1	1			

Machine (load)	VII					VIII				
	Worker					Worker				
	W1	W2	W3	W4	W5	W1	W2	W3	W4	W5
M1 (79.1)			1		1	1		1		1
M2 (72.8)	1	1		1		1		1	1	
M3 (64.7)	1	1		1			1	1		1
M4 (55.4)			1	1	1		1		1	1
M5 (47.5)	1	1		1		1	1		1	
M6 (40.4)	1		1		1		1		1	1
M7 (30.3)		1	1		1	1	1		1	
M8 (25.8)		1	1		1	1	1	1		
M9 (17.9)	1		1		1			1	1	1
M10 (6.1)	1	1		1		1				1

2.3. Routing structure

As previously stated, this study addresses routing structure as a contextual variable. We define three different routing structures: parallel, serial and job shop. With a parallel structure, part-types (or customers) must visit only one machine (server) out of a set of non-identical machines (servers) with different processing times. Each machine has its own queue of part-types, independent of other machines. In this way, routings do not contribute to interdependencies among machines. This situation can be found in many functional departments of manufacturing firms, as in a firm that produces plastic bottle tops using a number of different plastic molding machines. Parallel structures may also be easily identified among service systems, such as in call centers with multiple customer classes. Customers within each class arrive independently from one another and may be served by a dedicated (group of) server(s), while service times per class differ.

In a serial structure, part-types must visit all machines in a fixed order (machine 1, 2, ... n), representing an asynchronous flow line. The routing of the jobs creates interdependency among the machines. Since the routing is fixed, however, arrivals at machines other than the first are less variable than in a parallel structure. Finally, with a job shop structure, the number of machines that a part-type must visit and the order in which they must be visited will differ across part-types.

3. Simulation study

This section describes the simulation study used to evaluate the various configurations. As in all simulations, we have made a number of modeling assumptions concerning operational rules and stochastic behavior. First, we explain the experimental design by distinguishing parameters (fixed factors) and experimental factors. We then discuss the performance measures and provide details on how the simulation experiments were performed.

3.1. Experimental design

3.1.1. Fixed factors:

Design of the system, generation of job arrivals, and processing times

System size was already determined in the previous section: The DRC system consists of ten machines and five workers. Jobs arrive according to a Poisson distribution. We model differences in the utilization of machines (see Table 3) by specifying a different average processing time for each machine. The processing times at machines are distributed according to a 2-erlang distribution. Since mean and variability of processing times vary across machines, an unbalanced system is represented. In such a system, variability buffering becomes an important objective of cross-training. How well each configuration performs in simulation is determined partly by how well the configuration enables variability buffering.

Control of the shop

Because the system is dual-resource constrained, labor allocation rules must be specified. Traditional labor allocation rules in DRC systems are the “when” labor assignment rule, which determines when a worker is eligible for transfer, and the “where” labor assignment rule, which determines where a worker should be transferred to once he or she is eligible for transfer. Additionally, we specified a “who” labor allocation rule, which is often neglected in prior literature, but is necessary for proper operation of the system. The who-rule decides which worker should be transferred to a machine when multiple workers are available to perform an operation at a machine, and no other machines are waiting for (one of) these workers.

In simulating the various configurations, we assume a centralized when-rule, meaning that workers are allowed to transfer to another machine after they have finished a job at a machine. By contrast, a decentralized when-rule requires that workers finish all jobs in front of the machine before they are allowed to transfer to another machine. Further, a First-In-System-First-Served (FISFS) where-rule is used to assign workers who are eligible for transfer to the machine with the “oldest” job in the queue. Jobs are also dispatched according to the FISFS rule, meaning that the oldest job at a machine is processed first. In this way, the where-rule collaborates with the dispatching rule, in that the where-rule sends the worker to the machine with the oldest job in the queue, while the dispatching rule picks the oldest job from that queue to be processed first. We used the “longest idle time” who-rule, which assigns the worker who has been idle the longest time when more workers are available for a job. This rule attempts to equalize the workloads of workers, and was also employed by Rochette and Sadowski (1976).

It is conceivable that the labor allocation rules we have chosen perform differently within each routing structure, or even within each cross-training configuration. For instance, within the serial structure, the FISFS where-rule is likely to transfer a worker from a job processed on the bottleneck machine to the next machine, possibly leaving the bottleneck machine unstaffed. Instead, it may be advantageous to make sure that the bottleneck is staffed, if necessary, by giving it priority over the other machines in the line. Ideally, optimal labor allocation rules should be designed for each cross-training configuration. For example, in their comparison of the cherry picking and D-skill chaining skill pattern strategies within a serial environment, Hopp *et al.* (2002) designed optimal allocation policies, and chose the best heuristic for each strategy. Since the focus of this study is not

on operating rules, however, we choose simple worker allocation rules which have been used previously –in both research and practice – and did not allow them to vary over configurations or routing structures.

Absenteeism

Harrison and Price (2003) define absenteeism as the lack of an individual's physical presence in a behavioral setting where that individual is expected to be. Defined in this way, vacation and other planned absences are excluded from the absenteeism rate. We model only short, temporary absenteeism (1-5 days), since the consequences of this type of absence are much more disruptive than are those of medium, long-term or planned absenteeism. This is so, because companies often compensate for absences of more than one week – or of scheduled absences – by such actions as hiring temporary replacements. Short temporary absenteeism is modeled such that a worker is absent during fractions (an average of four percent) of the simulation time and resumes work after each absence. For this, both duration and frequency of absences must be specified. The duration of absenteeism for each worker is distributed according to a discrete uniform distribution with values from one to five days. The frequency of absenteeism per worker is distributed according to a negative exponential distribution with an average time between absences of 75 working days. In one year (207.5 days), each worker is therefore absent an average of 2.76 times with an average duration of three days, resulting in an absenteeism rate of four percent.

3.1.2. Experimental factors

For the simulation, two experimental factors with different levels are examined: cross-training configuration (eight levels) and routing structure (three levels).

Cross-training configuration

The eight cross-training configurations depicted in Table 3 result from a 2x2x2 full factorial design of multi-functionality, machine coverage, and collective responsibility (see Table 1).

Routing structure

Within the parallel structure, each part-type visits one of the ten machines randomly. Within the serial structure, all part-types must visit all machines in a fixed order (Machine 1, 2, ... 10). Finally, within the job shop structure, the routing length of part-types is uniformly distributed between one and ten machines, while the order of the routing steps is random.

3.2. Performance measures and simulation details

Performance is measured as the mean flow time of jobs through the system (MFT) and standard deviation of the workload distribution of the five workers (SD_{workload}). MFT can be seen as a measure of the operational performance of the system, and relates to the speed and delivery performance of manufacturing teams. Almost all simulation studies include MFT as a major performance measure. SD_{workload} relates to the social dimension of a manufacturing team. The higher the standard deviation, the more variation there will be in the workloads of the various workers. Because of the pressure toward equity, workers in a manufacturing team will attempt to ensure as little variation as possible in the distribution of the workload. The chained graph (as described in Section 2) allows for such strategies. A

highly varied workload, however, can be the result of specific labor allocation rules that focus on minimizing queuing times. In these situations, workers' attempts to equalize the workload through social interaction will tend to have a negative influence on MFT. A management decision to accept a highly variable workload carries with it the risk of future dissatisfaction among workers with regard to the workload.

The simulation models were written in the object-oriented simulation software package EM-Plant Version 5.5 (Stuttgart: Technomatix). The simulation models used are stochastic, steady-state, and non-terminating. We used the replication-deletion approach (Law and Kelton 2000: 525) to estimate the steady-state means of the output parameters. We employed Welch's method in order to determine the warm-up period. Other graphical approaches were used to gain insight into the number of replications and the run length required. Each experiment consisted of 35 replications with a run length of 70,000 time units and a warm-up period of 10,000 time units. Different seeds were used for each replication to maximize sampling independence.

4. Results

The data were analyzed by means of Analysis of Variance (ANOVA). We analyzed each routing structure independently, as the results of these contexts are not directly comparable. It is likely that the mean flow time of jobs depends on the length of the routings, which is different in each structure. We do, however, compare the relative performance of cross-training policies across the three routing structures, in order to indicate the extent to which good cross-training policies are robust within different routing structures.

We consider the dependent variables, mean flow time and standard deviation of the workload distribution, separately. Since the eight cross-training configurations used in the simulation are the result of a 2x2x2 full factorial design of the aspects multi-functionality, machine coverage and collective responsibility, we treat each of these aspects as an independent variable having two levels. This is preferable to treating the experimental variable "cross-training configuration" as a single independent variable having eight levels, as it allows for the consideration of interaction effects. The following section discusses the simulation results within each of the three routing structures.

4.1. The parallel structure

Table 4. ANOVA results for the parallel structure

PARALLEL STRUCTURE				
Source	Mean Flow Time		SD workload	
	F	p-value	F	p-value
MF	419.85	p < 0.001	17085.24	p < 0.001
MC	331.09	p < 0.001	772.26	p < 0.001
CR	3.37	p = 0.001	581.84	p < 0.001
MF x MC	269.02	p < 0.001	1454.72	p < 0.001
MF x CR	6.07	p < 0.001	119.61	p < 0.001
MC x CR	0.89	p = 0.087	45.73	p < 0.001
MF x MC x CR	2.095	p = 0.009	8.66	p = 0.004

Table 4 shows the ANOVA results for MFT and SD_{workload} . For both MFT and SD_{workload} , the homogeneity of variance assumption does not hold (Levene test, $p < 0.05$). The F statistic, however, is robust against heterogeneous variances, as long as the group sizes are equal (Glass *et al.* 1972) or approximately equal (Stevens 1996: 249). Because between-subjects ANOVAs are conducted with equal cell sizes, we continue the analyses. Table 4 shows the main effects and most of the interaction effects to be significant ($p < 0.05$) for both MFT and SD_{workload} .

4.1.1. Mean flow time within the parallel structure

The significant main effect of multi-functionality in Table 4 indicates that the difference in MFT between equal and unequal multi-functionality is significant. The mean flow times for equal and unequal multi-functionality are 6.29 and 8.73, respectively. As expected, in a situation without learning effects and with absenteeism, equal multi-functionality is preferable to unequal multi-functionality.

The significant main effect of machine coverage indicates that configurations with equal machine coverage perform better (MFT=6.42) than do configurations with unequal machine coverage (MFT=8.60). Finally, the main effect of collective responsibility indicates that maximizing collective responsibility results in better performance (MFT=7.40) than does minimizing collective responsibility (MFT=7.62).

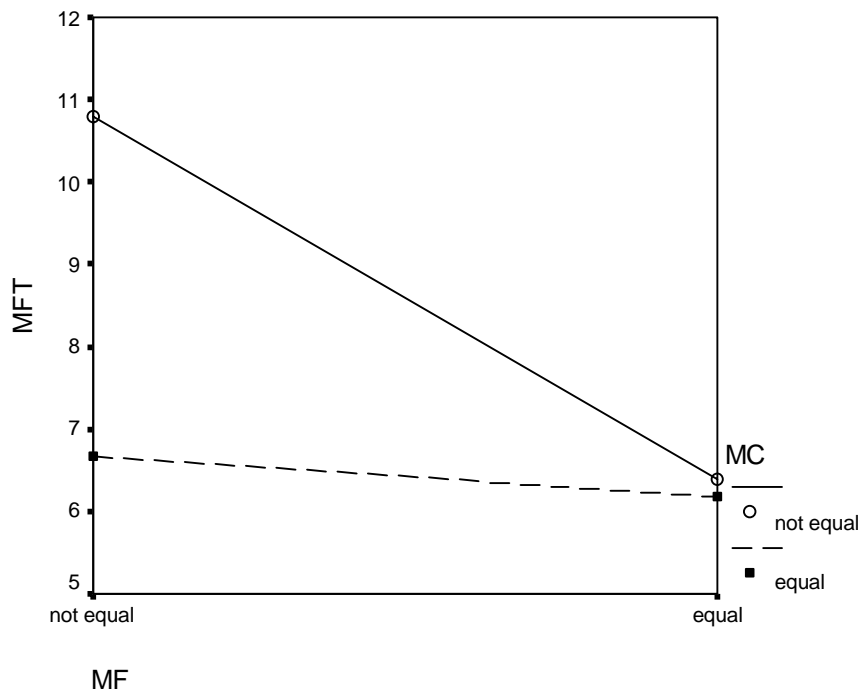


Figure 2. Interaction effect of multi-functionality and machine coverage (MF x MC) with respect to mean flow time (MFT) within the parallel structure

The relatively large interaction effect of multi-functionality with machine coverage (MF x MC) indicates that the MFT performance effect of multi-functionality depends on the level of machine coverage, as shown in Figure 2. Although the simple main effects of multi-functionality show its effect on MFT to be significant ($p < 0.05$) within both levels of machine coverage, the effect is much stronger under the condition of unequal than of equal machine coverage. There seems to be a substitute effect between multi-functionality and machine coverage. The worst performance is observed when both multi-functionality and machine coverage are unequal (MFT=10.81). With unequal multi-functionality, skills are concentrated at two workers, and with unequal machine coverage, skills are concentrated at a few machines. The combination of unequal multi-functionality and unequal machine coverage seems to result in cross-training configurations in which a few machines can be operated by all workers (the result of unequal MC), while the remaining machines can be operated by only two workers (the result of unequal MF). In such a situation, the workloads of the two highly multi-functional workers will thus be heavy, especially if they are also assigned to the machines with high machine coverage, thus blocking these machines for workers with few other skills. If one of these two independent variables is equalized, MFT performance improves drastically (equal MF: MFT=6.39; equal MC: MFT=6.67).

When machine coverage is equalized and multi-functionality remains unequal, most skills are concentrated on two workers, but the remaining skills are divided equally among machines. This means that tasks of the three least multi-functional workers do not overlap. When multi-functionality is equalized and machine coverage remains unequal, most skills are concentrated on a few machines, but the remaining skills are equally divided among workers. Equalizing both multi-functionality and machine coverage results in the best performance (MFT=6.18), but the improvement is small compared to equalizing only one of these variables.

For the interaction effect of multi-functionality with collective responsibility (MF x CR), the simple main effects of multi-functionality show a significant effect on MFT ($p < 0.05$) within both levels of collective responsibility. The effect seems to be stronger, however, in the case of minimum collective responsibility, as illustrated in Figure 3. When collective responsibility is at a minimum, overlapping skills tend to be placed at machines with low workloads. If multi-functionality is unequal, the remaining skills for the three least multi-functional workers will thus be placed at machines with low workloads, thus increasing the workload for the two highly multi-functional workers. Equalizing multi-functionality in this case will result in more improvement than will equalizing multi-functionality in a situation where the remaining skills are divided among heavily utilized machines. The simple main effects of collective responsibility reveal no significant effect on MFT ($p = 0.419$) under the condition of equal multi-functionality.

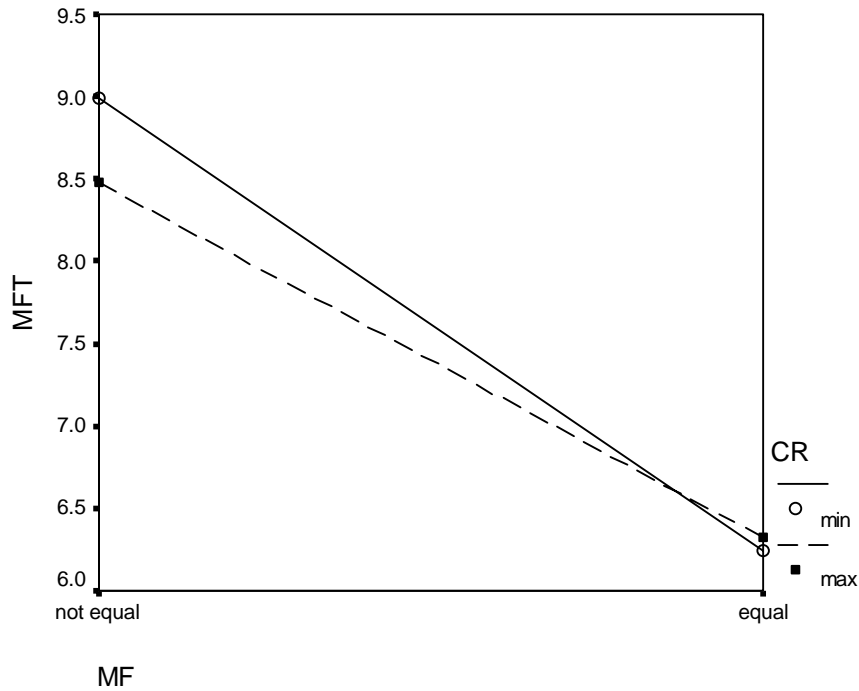


Figure 3. Interaction effect of multi-functionality and collective responsibility (MF x CR) with respect to mean flow time (MFT) within the parallel structure

The three-way interaction effect is significant as well (see Table 4). Table 5 shows the full factorial results of multi-functionality, machine coverage, and collective responsibility (MF x MC x CR) on MFT and SD workload. Each combination of the three independent variables represents a cross-training configuration. The mean flow time of the worst performing configuration (V) is 81.5 percent higher than that of the best performing configuration (VII). These results suggest that the selection of the most appropriate configuration is an important task for a manager who is responsible for cross-training the workforce.

Table 5. Full factorial results for MFT and SD workload within the parallel structure

MF	MC	CR	Configuration	MFT	SD workload
not equal	not equal	min	V	11.20	0.0693
		max	VI	10.40	0.0586
equal	equal	min	I	6.78	0.0480
		max	II	6.55	0.0346
	not equal	min	III	6.32	0.00649
		max	IV	6.45	0.00529
equal	equal	min	VII	6.17	0.0134
		max	VIII	6.19	0.00551

The simple-simple main effects of machine coverage reveal no significant effect on MFT ($p = 0.241$) under the condition of equal multi-functionality and minimum collective responsibility. A significant effect ($p = 0.037$) does exist, however, under conditions of equal multi-functionality and maximum collective responsibility. In other words, equalizing machine coverage when multi-functionality is already equal results in better MFT only if the skills with unequal machine coverage are concentrated on heavily utilized machines (as in Configuration IV), instead of on machines with low workloads (as in Configuration III). The simple-simple main effects of collective responsibility show a significant effect on MFT ($p < 0.05$) only under conditions of unequal multi-functionality and unequal machine coverage. Configurations V and VI, which clearly show the worst performance, represent this situation. In other words, within the parallel structure, collective responsibility matters only in the choice between the two configurations having the worst overall performance (Configurations V and VI).

When either multi-functionality or machine coverage (or both) are unequal, there is no reason for concern about collective responsibility. Under conditions of equal multi-functionality and machine coverage, Configurations VII and VIII show the best MFT results.

4.1.2. SD workload within the parallel structure

From a human resource management perspective, multi-functionality appears to be the most important aspect to consider. With respect to the standard deviation of workload distribution, the F-value for multi-functionality (main effect MF, see Table 4) is relatively large compared to that of the other effects. The significant main effect of multi-functionality indicates that equal multi-functionality is better ($SD_{\text{workload}} = 0.00767$) than unequal multi-functionality ($SD_{\text{workload}} = 0.0526$). The main effect of machine coverage (MC) indicates that configurations with equal machine coverage perform better ($SD_{\text{workload}} = 0.025$) than do configurations with unequal machine coverage ($SD_{\text{workload}} = 0.035$). Finally, the main effect of collective responsibility indicates that maximizing CR results in better performance ($SD_{\text{workload}} = 0.026$) than does minimizing CR ($SD_{\text{workload}} = 0.034$). The results of the main effects for SD_{workload} are thus similar to those of MFT.

As shown in Figure 4, the significant interaction effect of multi-functionality with machine coverage (MF x MC) indicates that the effect of multi-functionality differs for each level of machine coverage. The simple main effect of multi-functionality on SD_{workload} is significant ($p < 0.05$) for both levels of machine coverage, but the effects seems stronger under the condition of unequal machine coverage. The simple main effect of machine coverage on SD_{workload} is significant ($p < 0.05$) for both levels of multi-functionality.

Equal machine coverage improves SD_{workload} under the condition of unequal multi-functionality. Equalizing machine coverage helps Workers 1 and 2 to share their workload more efficiently with the other workers. In contrast, unequal machine coverage is preferable under the condition of equal multi-functionality. In this condition, each worker is skilled for five or six machines. Workload imbalances are apparently better addressed by connecting each worker with the other workers through a few machines that they can all operate.

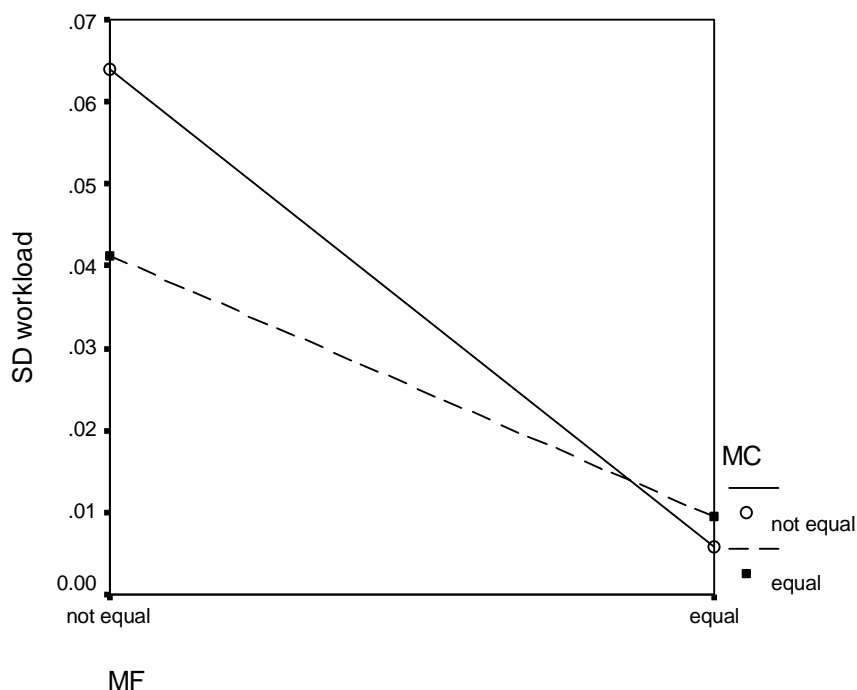


Figure 4. Interaction effect of multi-functionality and machine coverage (MF x MC) with respect to SD workload within the parallel structure

For the interaction effect of multi-functionality with collective responsibility (MF x CR), the simple main effect of multi-functionality on $SD_{workload}$ (equal multi-functionality decreases $SD_{workload}$ in comparison with unequal multi-functionality) is significant ($p < 0.05$) for both levels of collective responsibility, but is stronger under the condition of minimum collective responsibility. For the interaction effect of machine coverage with collective responsibility (MC x CR), the simple main effect of machine coverage on $SD_{workload}$ (equal machine coverage decreases $SD_{workload}$ values in comparison with unequal machine coverage) is significant ($p < 0.05$) for both levels of collective responsibility, but is stronger under the condition of maximum collective responsibility.

Configuration III performs better than configuration VII. The simple-simple main effects of machine coverage show that unequal machine coverage performs better ($p < 0.05$) than does equal machine coverage only under conditions of equal multi-functionality and minimum collective responsibility. These results suggest that workload imbalances are better addressed by connecting workers through a few machines that they can all operate and which have low workloads. Since workload differences among machines are based on differences in service times, only relatively small jobs are performed by lightly utilized machines. These small jobs help to balance the workload among workers. Under conditions of equal multi-functionality and maximum collective responsibility (Configurations IV and VIII), the effect of machine coverage is not significant ($p = 0.747$). The simple-simple main

effects of collective responsibility are not significant ($p=0.083$), under conditions of equal multi-functionality and unequal machine coverage (Configurations III and IV).

With respect to $SD_{workload}$, Configurations IV, VIII, and III perform best, as shown in Table 5. In these configurations, workers are able to divide the workload equally, which is perceived as being fair. Equal multi-functionality apparently contributes to such equitable workload distributions. The higher $SD_{workload}$ of Configuration VII can be explained by the fact that this configuration has too little team responsibility in order to equalize the utilization of the workers. Workers 3 and 5 have utilizations of 90 percent, while the others have utilizations of approximately 86.8 percent. These two workers are the only ones able to operate the most heavily utilized machine.

Configurations V, VI, I and II perform the worst with respect to $SD_{workload}$. These configurations all reflect conditions of unequal multi-functionality. Feelings of equity and interpersonal justice may be reduced by the fact that some workers possess more skills than others. Further, in these configurations, only two workers (Workers 1 and 2) have heavy workloads. These workers face a large number of requests from the various machines, resulting in utilizations of 95.5 percent in Configuration V, 94.4 percent in Configuration VI, 93.2 percent in Configuration I, and 91.7 percent in Configuration II. The inability to divide the workload equally may be perceived as unfair. Worker utilizations are much more balanced (around 88 percent) in the other configurations. Configurations V and VI, with both unequal multi-functionality and unequal machine coverage, perform the worst. The results of $SD_{workload}$ are, for the most part, similar to those of MFT.

4.2. *The serial structure*

Within the serial structure, Configurations I and V are excluded from the ANOVA analysis, since these configurations become unstable in simulation. This can be explained by the problematic combination of unequal multi-functionality and minimum collective responsibility within this structure. That is, in these configurations, the highly multi-functional Workers 1 and 2 are mainly responsible for heavily utilized machines (M1, for example, which is both the first machine in the line and the bottleneck machine), while also sharing responsibility for all the other machines. The other (much less multi-functional) workers predominantly share responsibility for machines with lower workloads. The result is that the workloads of Worker 1 and 2 become too high and Machine 1 is not able to process all arriving jobs due to the unavailability of appropriately skilled labor. This, in turn, results in an increasing queue and infinite flow times for Machine 1 in the long run.

Since Configurations I and V are excluded from further analysis, we cannot perform a full factorial analysis. Instead, we analyze the other combinations of factors with two designs. The first design includes Configurations III, IV, VII, and VIII, with equal multi-functionality. Machine coverage and collective responsibility are the independent variables in this design. The second design includes Configurations II and VI, under conditions of unequal multi-functionality and maximum collective responsibility. Machine coverage is the only independent variable remaining in this design.

Table 6 shows the ANOVA results for MFT and $SD_{workload}$ for both designs. Again, the homogeneity of variance assumption does not hold (Levene test, $p < 0.05$). Since we conduct between-subjects ANOVAs with equal cell sizes, however, the analysis may continue.

Table 6. ANOVA results for the serial structure

SERIAL STRUCTURE				
Source	Mean Flow Time		SD workload	
	F	p-value	F	p-value
DESIGN 1				
MC	0.14	p = 0.713	814.36	p < 0.001
CR	71.52	p < 0.001	1198.15	p < 0.001
MC x CR	1.89	p = 0.172	991.10	p < 0.001
DESIGN 2				
MC	55.60	p < 0.001	5.33	p = 0.024

4.2.1. Mean flow time within the serial structure

Within the first design, which considers configurations with equal multi-functionality, only the main effect of collective responsibility is significant ($p < 0.05$). Minimum collective responsibility results in much larger mean flow times (MFT=231.63) than does maximum collective responsibility (MFT=93.24). Configurations III and VII perform worst with respect to MFT, as only a few workers can operate the bottleneck machines. The choice to minimize collective responsibility results in higher coverage for machines with lower workloads. If collective responsibility is maximized (as in Configurations IV and VIII), more workers are able to operate the bottleneck machines and MFT performance is maximized.

Within the second design, with unequal multi-functionality and maximum collective responsibility, the effect of machine coverage is significant. Unequal machine coverage apparently leads to much better results (Configuration VI: MFT=65.58) than does equal machine coverage (Configuration II: MFT=256.44). In Configuration VI, all workers have the skills necessary to operate the most heavily utilized machines (Machines 1 and 2). Configuration II performs much worse, as only a few workers can operate the bottleneck machines, a result of striving for equal machine coverage. The primary substantive conclusion that can be drawn from these results is that, within the serial structure, managers should focus their cross-training policies on bottleneck machines. This can be realized by unequal machine coverage and maximum collective responsibility.

4.2.2. $SD_{workload}$ within the serial structure

Within the first design, which considers configurations with equal multi-functionality, the main effects of machine coverage and collective responsibility and the interaction effect are significant ($p < 0.05$). The significant main effect of machine coverage shows unequal machine coverage to be better ($SD_{workload} = 0.00670$) than equal machine coverage ($SD_{workload} = 0.0172$). The significant main effect of collective responsibility shows that maximizing collective responsibility is preferable ($SD_{workload} = 0.00558$) to minimizing collective responsibility ($SD_{workload} = 0.0183$).

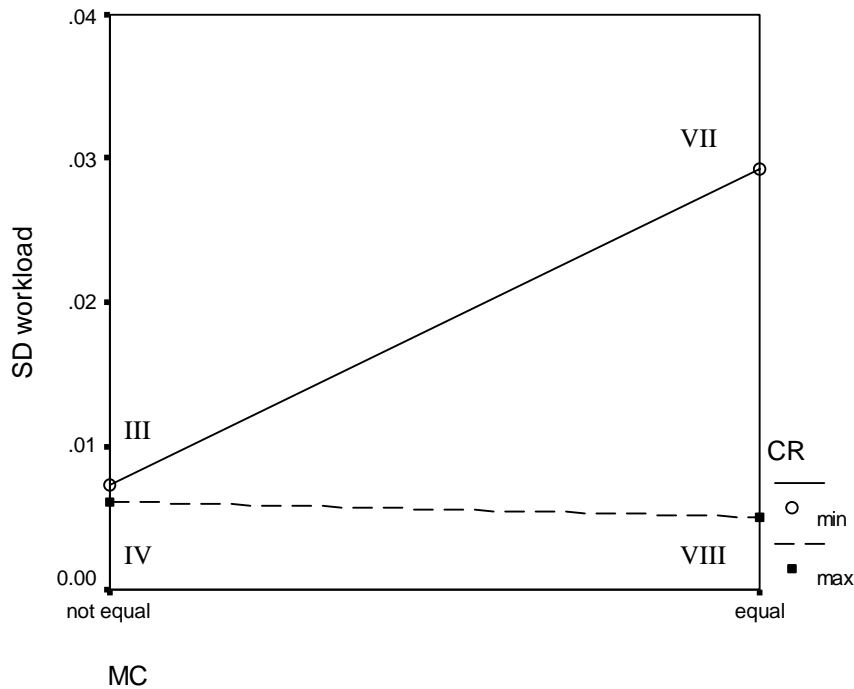


Figure 5. Interaction effect of machine coverage and collective responsibility (MC x CR) with respect to SD workload within the first design of the serial structure. The four points represent the four cross-training configurations III, IV, VII, and VIII.

Figure 5 shows the significant interaction effect of machine coverage and collective responsibility (MC x CR). The simple main effects of machine coverage show that the effect of machine coverage on $SD_{workload}$ is significant under the conditions of both minimum collective responsibility ($p < 0.05$) and maximum collective responsibility ($p = 0.039$), but larger for minimum collective responsibility. Within this first design, where multi-functionality is equal, maximizing collective responsibility is thus important for $SD_{workload}$, especially in case of equal machine coverage. If realizing maximum responsibility is problematic, unequal machine coverage should be sought in order to balance the distribution of the workload. Workers can then cope with workload imbalances, as they are connected through a few machines they can all operate. Within the first design of the serial structure, Configurations IV and VIII are best with respect to $SD_{workload}$. These configurations allow a balanced workload.

Within the second design, with unequal multi-functionality and maximum collective responsibility, the effect of machine coverage is significant ($p=0.024$) at a 0.05 level of significance. Unequal machine coverage is preferable ($SD_{workload} = 0.0578$) to equal machine

coverage ($SD_{\text{workload}} = 0.0598$). Configuration VI thus performs better with respect to SD_{workload} than does Configuration II.

A comparison of the configurations within Design 2 with those within Design 1 reveals that the configurations in Design 1 perform better with respect to SD_{workload} . Substantively, within the serial structure, equal multi-functionality is important for balancing workload distribution. Further, under conditions of equal multi-functionality, it is best to strive for maximum collective responsibility.

4.3. The job shop structure

Within the job shop structure, Configurations V and VI perform much worse than do the other configurations, as was also observed within the parallel structure. Within the job shop structure, they even cause the system to become unstable. These Configurations represent unequal multi-functionality and unequal machine coverage. Further, collective responsibility is minimized in Configuration V, while it is maximized in Configuration VI. Workers 1 and 2 are fully cross-trained, while the other workers have few skills, which overlap for machines with either low (as in Configuration V) or high workloads (as in Configuration VI). For Configuration V, the flow times of jobs through the first two machines are very high, while for Configuration VI, the flow times of jobs through Machines 5 to 10 are very high. This means that, in both configurations, Workers 1 and 2 cannot deal with their extremely high workloads. In order to improve performance, at least one of these two factors – multi-functionality or machine coverage – must be equal.

When Configurations V and VI are excluded, two designs can be created to analyze the other combinations of factors. The first design includes Configurations III, IV, VII, and VIII, all of which reflect equal multi-functionality. Machine coverage and collective responsibility are the independent variables in this design. The second design includes Configurations I and II, which reflect unequal multi-functionality and equal machine coverage. In this design, collective responsibility is the only remaining independent variable.

Table 7. ANOVA results for the job shop structure

JOB SHOP STRUCTURE				
Source	Mean Flow Time		SD workload	
	F	p-value	F	p-value
DESIGN 1				
MC	14.39	$p < 0.001$	130.79	$p < 0.001$
CR	6.25	$p = 0.014$	275.13	$p < 0.001$
MC x CR	0.06	$p = 0.807$	137.24	$p < 0.001$
DESIGN 2				
CR	102.32	$p < 0.001$	214.16	$p < 0.001$

Table 7 shows the ANOVA results for MFT and SD_{workload} for both designs. The homogeneity of variance assumption is met for SD_{workload} (Levene test, $p \geq 0.05$) in both designs, and for MFT within the first design.

4.3.1. Mean flow time within the job shop structure

Within the first design, which considers configurations with equal multi-functionality, the main effects of machine coverage and collective responsibility are significant ($p < 0.05$) but the interaction effect is not significant ($p = 0.807$). The significant main effect of machine coverage indicates that equal machine coverage is preferable (MFT = 24.90) to unequal machine coverage (MFT = 25.85). The significant main effect of collective responsibility indicates that minimizing collective responsibility is preferable (MFT = 25.06) to maximizing collective responsibility (MFT = 25.68). Minimizing collective responsibility reduces the overlap among the tasks of workers. The implication for this design, in which all workers possess the same number of skills (equal MF), is that workers who are able to operate bottleneck machines are less distracted by other tasks. Configuration VII performs best, therefore, with respect to MFT.

Within the second design, with unequal multifunctionality and equal machine coverage, the effect of collective responsibility is significant. In this situation, it is better to maximize collective responsibility (Configuration II: MFT = 27.13) than to minimize collective responsibility (Configuration I: MFT = 31.79). The performance of Configurations I and II, however, are inferior to that of the configurations within the first design. These results suggest the substantive conclusion that, within the job shop structure, equal multi-functionality, equal machine coverage and minimum collective responsibility are all important with respect to MFT.

4.3.2. SD workload within the job shop structure

Within the first design, both the main effects and the interaction effect of machine coverage and collective responsibility are significant ($p < 0.05$). The significant main effect of machine coverage indicates that unequal machine coverage ($SD_{\text{workload}} = 0.00594$) is preferable to equal machine coverage ($SD_{\text{workload}} = 0.0100$). A similar effect is found within the parallel structure. Under the condition of equal multi-functionality, workers appear better able to balance their workloads when there are a few machines that every worker can operate. The main effect of collective responsibility indicates that it is better to maximize collective responsibility ($SD_{\text{workload}} = 0.00502$) than to minimize collective responsibility ($SD_{\text{workload}} = 0.0109$). The interaction effect of machine coverage and collective responsibility (MC x CR) shows the same pattern as depicted in Figure 5.

Configurations IV and VIII perform best with respect to SD_{workload} . The simple main effects of machine coverage show that the effect of machine coverage on SD_{workload} is significant ($p < 0.05$) only in case of minimum collective responsibility. As within the parallel structure, workload imbalances are more appropriately addressed by connecting all workers by means of a few machines whose workloads are light. Under the condition of maximum collective responsibility, the effect is not significant ($p = 0.844$). These results lead to the substantive conclusion that, under conditions of equal multi-functionality, maximum collective responsibility should be sought. When this is not possible, unequal machine coverage should be sought as a means of balancing the distribution of the workload.

Within the second design, the effect of collective responsibility is significant ($p < 0.05$), suggesting that it is better to maximize collective responsibility ($SD_{\text{workload}} = 0.0416$) than to minimize collective responsibility ($SD_{\text{workload}} = 0.0549$). The performance of both Configurations I and II with regard to SD_{workload} , however, are inferior to those of the configurations within the first design.

4.4. Discussion

Within the parallel structure, it is important for MFT that either multi-functionality or machine coverage be equal. Configurations in which both of these components are equal (as in Configurations VII and VIII) perform the best. With respect to SD_{workload} , it is best to have equal multi-functionality and maximum collective responsibility (as in Configurations IV and VIII). Further, Configuration III, representing equal multifunctionality, unequal machine coverage and minimum collective responsibility also performs well in this respect. In this configuration, a few machines with low workloads connect all workers, enabling an effective management of workload imbalances. The goals of Operations Management and of Human Resource Management are integrated in Configuration VIII, which is the result of applying the cross-training policy of equal multifunctionality, equal machine coverage, and maximal collective responsibility.

Within the serial structure, reaching an optimal MFT requires a focus on bottleneck machines. Heavily utilized machines should receive much coverage. This is enabled by the combination of unequal machine coverage and maximum collective responsibility. Within the serial structure, therefore, Configurations IV and VI perform well with regard to MFT. With respect to SD_{workload} , equal multi-functionality is important and maximum collective responsibility is desirable.

The cross-training policy of equal multifunctionality, unequal machine coverage, and maximum collective responsibility, which is applied to create configuration IV, integrates the goals of both OM and HRM within the serial routing structure. Interestingly, although Configuration VI, representing unequal multifunctionality, unequal machine coverage, and maximum collective responsibility performs very well with regard to MFT, its performance with respect to SD_{workload} is among the worst. For this cross-training policy, the goals of OM come into conflict with those of HRM.

Within the job shop structure, equal multi-functionality, equal machine coverage, and minimum collective responsibility appear important for MFT. For SD_{workload} , equal multi-functionality and maximum collective responsibility should be the norm. If maximum collective responsibility is not possible, achieving an optimal degree of SD_{workload} requires unequal machine coverage, as this allows for balancing workloads among workers. In this routing structure, therefore, the goals of OM and those of HRM apparently cannot be integrated.

5. Conclusions

An important contribution of this paper is the identification of important aspects to be considered when developing a cross-training policy. These aspects are as follows: extent of cross-training, chaining, multi-functionality, machine coverage, and collective responsibility. A cross-training policy can be regarded as a set of rules dealing with these important aspects in order to determine how the skills of workers should be distributed. We developed an Integer Goal Programming (IGP) model to support a consequent application of alternative cross-training policies to manufacturing teams. It is conceivable that the IGP model forms a useful starting point for developing a decision support tool for cross-training policies in new situations. The IGP model can be solved using a weighted or a lexicographic approach. In this paper, we applied the lexicographic approach and applied one particular sequence of priorities. Further research is needed to explore the effect of

applying different sequences. Additionally, the effect of using the IGP model in different starting situations requires further investigation.

To evaluate the cross-training configurations within different routing structures, we performed a simulation study. The results give insight into the way in which a manager should address the aforementioned aspects in the development of cross-training policies within various routing structures. The results of the parallel and job shop structure point in the same direction. Within these routing structures, equal multi-functionality and equal machine coverage are important for achieving an optimal mean flow time. Within the serial structure, more attention should be paid to bottleneck machines. Here, the combination of unequal machine coverage and maximum collective responsibility results in good MFT performance. Within all routing structures, equal multi-functionality combined with maximum collective responsibility seems to enable a fair distribution of workload among workers. A good alternative within the parallel and job shop structure is equal multi-functionality combined with unequal machine coverage and minimum collective responsibility.

The results of this paper are based on a simulated setting with five workers and ten machines having different processing times (and thus different variability) and equal arrival rates of jobs per machine. Despite the limitations of this setting, we believe that the general conclusions as presented in this section hold for a broader spectrum of situations, although this should obviously be investigated in future research. Further, in the study presented here, labor allocation rules are not varied. It would therefore be worthwhile to study the effect of specific labor allocation rules, since tailor-made rules for each routing structure – or even for each configuration within each routing structure – may be able to redistribute workloads of workers and reduce flow time. All of the configurations that were excluded from the serial and job shop structures resulted in excessive workloads for Workers 1 and 2. Different rules for labor assignment could have possibly prevented this. Further, future research may pay attention to possible effects of varying system size, workload distribution on machines (including differences in processing time or differences in arrival rates of jobs to machines, or both), and variability of processing times per machine, on cross-training policy decisions.

This paper is a conceptual paper. It would be useful, therefore, to compare the alternative rules with respect to important aspects in a cross-training policy we have studied here with the rules that are made in actual practice. Also of interest would be an investigation of the degree to which the cross-training policies determined to be attractive by our model are consistent with current management practice.

Finally, this paper has approached the issue of cross-training from an operations management (OM) and a human resource management (HRM) viewpoint. Even though the focus of cross-training policies depends on the viewpoint considered, cross-training policies can be found that integrate both sets of goals within parallel and serial structures. Such integration within a single cross-training policy is more difficult within the job shop structure.

Acknowledgments

The authors are grateful to two anonymous referees for their helpful suggestions for improving an earlier version of the paper.

References

- Ashkenas, R., Ulrich, D., Jick, T., and Kerr, S., 1995, *The boundaryless organization* (San Francisco: Jossey-Bass Publishers).
- Austin, W., 1977, Equity theory and social comparison processes, in Suls, J.M. and Miller, R.L. (Eds.), *Social Comparison Processes: Theoretical and Empirical Perspectives*, Hemisphere, Washington, DC.
- Brusco, M.J. and Johns, T.R., 1998, Staffing a multiskilled workforce with varying levels of productivity: An analysis of cross-training policies. *Decision Sciences*, 29, 499-515.
- Campbell, G.M., 1999, Cross-Utilization of workers whose capabilities differ. *Management Science*, 45(5), 722-732.
- Clark, J., 1993, Full flexibility and self-supervision in an automated factory, in J. Clark (Ed.), *Human Resource Management and technical change*, Cornwell Press Ltd, Broughton Gifford, pp.116-136.
- Fazakerley, G.M., 1976, A research report on the human aspects of group technology and cellular manufacture. *International Journal of Production Research*, 14, 123-134.
- Felan, J.T. and Fry, T.D., 2001, Multi-level heterogeneous worker flexibility in a Dual Resource Constrained (DRC) job-shop. *International Journal of Production Research*, 39(14), 3041-3059.
- Fry, T.D., Kher, H.V., and Malhotra, M.K., 1995, Managing worker flexibility and attrition in dual resource constrained job shops. *International Journal of Production Research*, 33, 2136-2179.
- Glass, G.V., Peckham, P.D., and Sanders, J.H., 1972, Consequences of failure to meet assumptions underlying the fixed effects analysis of variance and covariance. *Review of Educational Research*, 42(3), 237-288.
- Harrison, D.A. and Price, K.H., 2003, Context and consistency in absenteeism: studying social and dispositional influences across multiple settings. *Human Resource Management Review*, 13, 203-225.
- Hopp, W.J., Tekin, E., and Van Oyen, M.P., 2002, Benefits of skill chaining in serial production lines with cross-trained workers. Working paper, Department of Industrial Engineering and Management Sciences, Northwestern University, Evanston, IL.
- Jackson, S.E., 1996, The consequences of diversity in multidisciplinary work teams, in M.A. West (Ed.), *Handbook of Work Group Psychology*, John Wiley and Sons Ltd, New York.
- Jellison, J. and Arkin, R., 1977, Social comparison of abilities: a self-presentation approach to decision making in groups, in Suls, J.M. and Miller, R.L. (Eds.), *Social Comparison Processes: Theoretical and Empirical Perspectives*, pp.235-257, Hemisphere, Washington, DC.
- Jordan, W.C. and Graves, S.C., 1995, Principles on the benefits of manufacturing process flexibility. *Management Science*, 41, 577-594.
- Kerr, N.L. and Bruun, S.E., 1983, Dispensability of member effort and group motivation losses: free-rider effects. *Journal of Personality and Social Psychology*, 44, 78-94.

Kher, H.V. and Malhotra, M.K., 1994, Acquiring and Operationalizing Worker Flexibility in Dual Resource Constrained Job Shops with Worker Transfer Delays and Learning Losses. *Omega*, 22, 521-533.

Latané, B., Williams, K., and Harkins, S., 1979, Many hands make light work: the causes and consequences of social loafing. *Journal of Personality and Social Psychology*, 37, 822-832.

Law, A.M. and Kelton, W.D., 2000, *Simulation Modeling and Analysis* (New York: McGraw-Hill).

Malhotra, M.K., Fry, T.D., Kher, H.V., and Donohue, J.M., 1993, The impact of learning and labor attrition of worker flexibility in dual resource constrained job shops. *Decision Sciences*, 24(3), 641-663.

Molleman, E. and Slomp, J., 1999, Functional Flexibility and Team Performance. *International Journal of Production Research*, 37, 1837-1858.

Park, P.S. and Bobrowski, P.M. (1989) Job Release and Labor Flexibility in a Dual Resource Constrained Job Shop. *Journal of Operations Management*, 8, 230-249.

Pennathur, A., Mital, A., Rajan, V., Kaber, D., Ray, P., Huston, R., Thompson, D., Markle, G., Pitman, M.A., Bishu, R., Crumpton, L., Deivanayagam, S., Fernandez, J., Mcelwee, M., McMulkin, M., and Sule, D., 1999, A Framework for training workers in contemporary manufacturing environments. *Int. J. Computer Integrated Manufacturing*, 12(4), 291-310.

Rochette, R. and Sadowski, R.P., 1976, A statistical comparison of the performance of simple dispatching rules for a particular set of job shops. *International Journal of Production Research*, 14(1), 63-75.

Stevens, J., 1996, *Applied multivariate statistics for the social sciences* (Mahwah, NJ: Lawrence Erlbaum Associates Inc.).

Treleven, M., 1989, A review of dual resource constrained systems research. *IIE Transactions*, 21, 279-287.

Wilke, H.A.M. and Meertens, R.W., 1994, *Group performance* (London: Routledge).