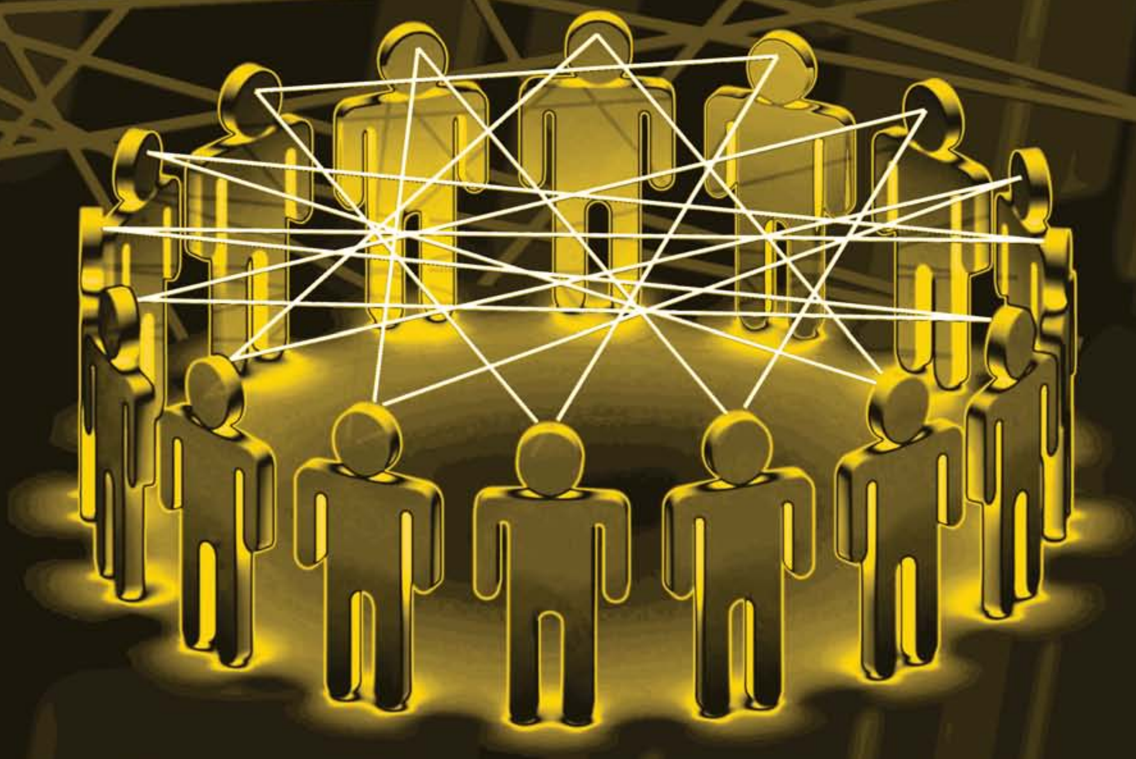
WORKFORCE CROSS TRAINING



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David A. Nembhard

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Preface

The idea for this project began many years ago as I started to conduct research in the area of workforce cross training. Several industrial managers and researchers began contacting me to ask about the body of knowledge in this area. Of course, many organizations have current or planned programs for cross training employees, yet few clear guidelines exist for designing these programs effectively with a focus on productivity and performance. For those who inquired, I was able to point them to a few research papers, but in the process I realized that there was a dearth of material that aggregated what was currently known, synthesized best practices, or even gave a clear indication of what was well known or not well known in this area. This book is intended to be a modest step toward that end.

This book integrates academic work on workforce cross training, current practices, and discussion of future needs and opportunities. It is not intended to be a comprehensive clearinghouse of all the work that has been done in the field. Rather, I hope the descriptions of best practices, effective research models, and results will be of benefit to both the interested researcher and the practitioner. It is through the gracious participation of the contributing authors that this project has been possible. For this I offer my heartfelt thanks. I believe that their varied viewpoints, approaches, and skill sets have resulted in a wide-ranging discussion of workforce cross-training technology. I hope that this book can serve as one of perhaps a number of starting points, where we can progress toward a better understanding of some of the how, why, when, who, and what that are involved in managing and improving workforce cross-training systems.

Acknowledgment

I would like to thank all of those who were involved with this project, first and foremost, the contributing authors, whose efforts are greatly appreciated, and the team at Taylor & Francis Group, Cindy Carelli and Jessica Vakili, for helping to get this project rolling, understanding delays, and keeping me on schedule. I also thank the National Science Foundation for its support of my research in this area, and specifically portions of my research that are summarized herein.

The Editor

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section I

Workforce operations

chapter 1

Design and operation of a cross-trained workforce

Jos A. C. Bokhorst and Jannes Slomp

Contents

1.1 Introduction

Due to increased global competition, firms are under constant pressure to cut their costs, while having to improve their delivery speed, quality, flexibility, and dependability. It has become clear that improvements should focus not only on the efficiency and effectiveness of (technical) processes but also on the workers involved in these processes. Workers increasingly need to be flexible — able to do several tasks and assume tasks or help other workers with their tasks — while remaining efficient and motivated. Acknowledging the value of the workforce and carefully considering the design and operation of a firm's workforce can significantly contribute to the improvement of the objectives of the firm. "Human capital" is a key success factor nowadays, and firms must try to achieve a fit between their own goals and the goals of their workforce. Training workers and using the acquired skills effectively is one of the ways both goals can be achieved.

In essence, a cross-trained workforce consists of (one or more teams of) workers who have (partly) overlapping skills or tasks they are able to perform. Research on cross training within the field of Operations Management often entails comparing the performance of teams having alternative numbers and/or distributions of skills, where the focus then is more on performance implications of the result of training — the qualifications — than on the process of training. Furthermore, even though a cross training may be regarded as the result of training someone for a skill already mastered by someone else (an overlapping skill), the terms *training* and *cross training* are more often used interchangeably. In this chapter, we also focus on the result of training instead of on the process, and we do not particularly distinguish a *cross training* from any other *training* or qualification.

This chapter focuses on the development of effective cross-training policies and labor assignment rules. These issues play a large role in Dual Resource Constrained (DRC) systems. In DRC systems, two resources are considered to be constraining factors for the level of output. In this chapter, we consider labor and machines to be the two constraining resources of our concern. This type of DRC system is also called a labor and machine-limited system, as opposed to a machine-limited system in which only machines are the constraining factor. In a labor and machine-limited system, jobs can only be processed if both a machine and a skilled worker are available. A key characteristic of labor and machine-limited systems is that the number of workers is less than the number of machines, which implies that (some) workers need to be multifunctional and worker transfer between machines is necessary. For smooth operation of these systems, attention should be given to cross training and labor assignment rules.

Table 1.1 An Example of a Skill Matrix

Machines workers	1	2	3	4	5	6	7	8	9	10
A		X		X		X				
B	X	X								X
C	X		X					X		
D		X		X	X				X	
E					X	X				X
F		X	X	X			X	X		
G		X					X			

Note: X denotes a skill.

Cross-training policy is defined as a set of rules for determining the extent of training and the distribution of workers' skills in a team. In practice, many firms use a skill matrix (also known as a worker–machine matrix or worker–task matrix) to display the current set of skills available in a team. Table 1.1 shows an example of a skill matrix, where each column represents a machine (a total of 10 machines) and each row represents a worker (a total of 7 workers in the team). An *X* in the matrix represents a worker skill. From the matrix, it is easy to see which skills a particular worker has mastered by looking at the corresponding row. For instance, worker A is skilled for machines 2, 4, and 6 in the example in Table 1.1. Similarly, by looking at a specific column, it can easily be seen which workers master the corresponding machine (for instance, machine 9 can only be operated by worker D).

Applying a cross-training policy to a manufacturing team results in an optimized skill matrix indicating which workers should be trained for which machines. We call the resulting changed skill matrix a *cross-training configuration*, which represents a cross-trained workforce. When having a cross-trained workforce, labor assignment rules must be set to properly assign workers to machines or tasks for which they are skilled.

Having a cross-trained workforce may support an organization's strategy, if carefully designed and operated. The extent and distribution of cross training impacts the performance of the workforce, as well as the assignment rules that are chosen to assign skilled workers to machines or tasks. Hopp and Van Oyen (2004) developed a strategic assessment framework that structures the key direct and indirect mechanisms by which a cross-trained workforce can support organizational strategy. They state that the *cross-training skill pattern* (cross-training configuration) and the *worker coordination policy* (labor assignment rule) may impact labor productivity, responsiveness, internal/external quality, and the offerings of products/services, which directly impact strategic objectives, such as cost, time, quality, and variety. Furthermore, issues with respect to team structure, such as collaboration, authority, communication, incentives, etc., indirectly impact the strategic objectives.

This chapter embraces an Operations Management viewpoint on cross training and labor assignment. Other aspects (i.e., human factors) are referred to and play a role in choices and considerations but are not dealt with in the research-based parts of the chapter. Time and costs are the main strategic objectives we consider.

Section 1.2 deals with the development of effective cross-training policies. Developing cross-training policies involves deciding which strategic goals to support, which aspects are important to include, and also defining decision rules to specify how these aspects will be addressed. Among the aspects considered are the extent of cross training, chaining, the level and distribution of multifunctionality and redundancy, and collective responsibility. These terms will be explained later in the chapter. We show how an Integer Goal Programming model can support making effective cross-training decisions. We evaluate cross-training decisions, or policies, by means of a simulation study. Finally, we show the applicability of an Integer Programming Model that — besides operational performance — focuses more on the training costs in an industrial setting.

Section 1.3 deals with labor assignment, which is addressing the question of which rules should be designed to assign workers to tasks for maximum performance. Here, the qualifications of workers or the tasks they are able to perform are fixed, but different labor assignment rules are designed that may alter the deployment of these qualifications. We first focus on industrial practice with respect to worker assignment. We then review the literature on labor assignment and worker differences. Previous studies on labor assignment mostly study the "when-rule" and "where-rule," which decide when a worker is eligible for transfer and where he/she should be transferred to, respectively. Furthermore, most studies consider a homogeneous workforce, or workers who have the same characteristics. In Section 1.3, we also draw attention to the "who-rule." This rule has gained only limited attention in literature so far. Finally, by means of several simulation experiments, we investigate labor assignment rules in systems with worker differences.

Section 1.4 discusses future research issues. The section extends the issues dealt with in Section 1.2 and Section 1.3 but also covers a broader range of (Operations Management) issues related to cross training and worker assignment that need to be addressed.

1.2 Development of cross-training policies

By developing a cross-training policy, an organization strives to design a cross-trained workforce that will support its strategy. Developing cross-training policies involves deciding which performance measures should be targeted, which aspects are important to include in light of this performance, and also defining decision rules to specify how these aspects will be addressed. The set of aspects to be included or the relative importance to be given to the aspects may depend on the specific strategy of the organization and the context.

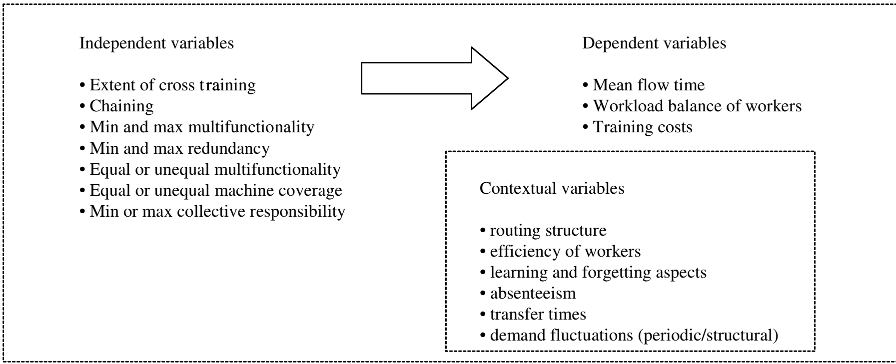

Figure 1.1 A model on developing and evaluating cross-training policies.

The following are five important aspects to consider when developing a cross-training policy: the extent of cross training, the concept of *chaining*, multifunctionality, machine coverage, and collective responsibility. Applying a cross-training policy to an existing workforce results in recommendations as to which workers to train for which tasks. This resulting cross-training configuration may be evaluated by using simulation. Figure 1.1 represents the theoretical model with the independent variables (aspects to consider), dependent variables (performance measures), and contextual variables.

Section 1.2.1 deals with performance measures and the contextual variables. The aspects to be considered in the development of a cross-training policy will be discussed consecutively in Section 1.2.2. Section 1.2.3 shows how an Integer Goal Programming model can lend support in making effective cross-training decisions and evaluates cross-training policies in a specific situation by means of simulation. Section 1.2.4 shows the applicability of an Integer Programming Model that focuses on the tradeoff between training costs and operational performance in an industrial setting. Finally, Section 1.2.5 summarizes the above discussions.

1.2.1 Performance measures and contextual factors

As mentioned in the Introduction, we embrace an Operations Management viewpoint and mainly focus on improving time (mean flow time of jobs) and costs (training costs and operational costs). We also consider the workload balance of workers to be an important measure from a Human Resource Management point of view. Of course, there are other reasons to perform cross training — both from a worker's point of view and a firm's point of view. A worker, for example, may be motivated more if his/her desire to be all round is fulfilled. A firm, for instance, may require extra training to decrease the frequency of entity handoffs in order to enable the workforce to develop broad capabilities that provide better ways of meeting customer needs (Hopp and VanOyen, 2004).

Several factors may be considered contextual variables. By this, we mean that these factors differ depending on the context of the workforce and may have an impact on (the relation between) independent and dependent variables. With respect to jobs, the routing of the jobs (i.e., routing structure: parallel, serial, job shop) has an impact on how to cross train workers (see Bokhorst et al., 2004b, and Section 1.2.3.2). Also, the complexity of tasks required to process the job or the variance in complexity between different tasks may impact cross-training decisions. The complexity of a task is most likely related to the amount of training costs and the specific learning and forgetting effects. That is, complex tasks may require more intensive training programs and/or a longer period of on-the-job learning than simple tasks, leading to higher investments for a company. Further, complexity significantly affects learning/forgetting parameters (of manual tasks), and the effects depend on the experience of workers (Nembhard, 2000). With respect to workers, several factors may or may not be included, e.g., the efficiency of workers, learning and forgetting aspects, absenteeism, and transfer times. Finally, with respect to the demand for machines, periodic and/or structural fluctuations may be considered.

We are interested in contexts where cross training leads to operational advantages, but at the same time involves significant training costs. In these situations, real tradeoffs have to be made. Section 1.2.3 focuses more on operational advantages and includes routing structure as a contextual variable and absenteeism and periodic demand fluctuations as given context. Section 1.2.4 presents a model that pays more attention to training costs and includes static efficiency differences between workers and several absenteeism scenarios as given context.

1.2.2 Important aspects to consider in developing cross-training policies

This subsection describes important aspects to consider when developing a cross-training policy. Throughout the discussion of important aspects, we will make use of an illustrative example. A cross-training configuration, which shows the distribution of skills within the workforce, can be represented by a worker–machine matrix or a bipartite graph, for instance. For the illustrative example, Figure 1.2 shows an initial cross-training configuration, representing four workers (A to D) and seven machines (I to VII) connected by worker skills. The graph is bipartite, since it can be partitioned into two disjoint subsets of vertices (i.e., workers and machines) such that each edge connects a worker to a machine. In this representation, the edges represent worker skills. Worker A is trained for machines I and II; worker B is able to operate machines III, IV, and V; worker C is qualified to operate machines V and VI; and worker D is trained for machines V and VII. The machine loads, which indicate the percentage of time in which the machines have to be used by the workers, are shown in brackets in Figure 1.2.

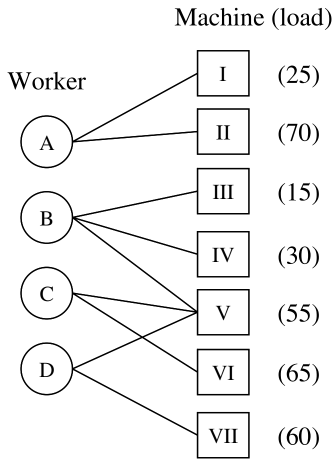

Figure 1.2 Initial cross-training configuration of the illustrative example.

1.2.2.1 Extent of cross training

A first aspect to consider when developing a cross-training policy is the extent of cross training required in the team. By the extent of cross training, we mean the number of (additional) cross trainings that are needed in the manufacturing team. A complete bipartite graph (i.e., each worker is connected to every machine) represents full flexibility. In case the bipartite graph is not complete, as in Figure 1.2, there is limited flexibility. Figure 1.2 shows limited flexibility, with 9 out of a possible 28 skills with full flexibility. 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 full flexibility.

Full flexibility is not needed, nor is it desirable in practical situations. Since it requires training of all workers for all machines, it can be very 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 workstations, to access information about the job to be performed at the new machine, and to learn or relearn the setup procedures. This is especially the case if the firm applies a centralized assignment rule (i.e., a worker reassignment is considered after completion of each job). The effect is less in the case of a decentralized rule, i.e., where a worker reassignment is considered only when the job queue is empty. In both cases, however, productivity loss due to an increase in the number of worker transfers 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 et al., 1993; Hut and Molleman, 1998).

In a cross-training policy, a value may be set for the *ideal* number of cross trainings in the desired cross-training configuration. Another option is to minimize the number of additional trainings or training costs, or to minimize the deviation of a budget for training set by a company. In our illustrative example, we assume that the minimization of the number of additional worker skills is a major objective. In practice, managers strive to balance the positive performance effects of cross training and the integral costs of additional worker skills.

1.2.2.2 The concept of chaining

In the initial cross-training configuration (Figure 1.2), we see that worker A is occupied for 95% of the time, since he/she is responsible for machines I and II. Workers B, C, and D are, on average, busy 75% of the time. The load on machine V can be used to balance the workload of workers B, C, and D. We assume that the objective of the firm in the example is to minimize flow times of jobs and to optimize the labor situation through further cross training of the workers. A first concern in the initial cross-training configuration is the unequal workload of the workers. Worker A is clearly the bottleneck, so it is likely that most queuing time will arise at machine I or II. The initial cross-training configuration does not permit a shift of work from worker A to B, C, or D. In the terms of Lau and Murnighan (1998), the initial distribution of skills is a potential *fault line* in the team. The graph is not connected, since there is no path that connects every pair of vertices. In order to enable such a path, at least one additional worker skill is needed.

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. (2004) 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. Hopp et al. (2004) showed that the two-skill chaining strategy is potentially robust and efficient in obtaining workforce agility in serial production lines.

Figure 1.3 shows, by means of a bold line, that worker B is additionally trained for machine II. This enables an equal workload division among the workers. This step can be regarded as a capacity-balancing step (Hopp et al., 2004), since cross training is used here to remove a structural imbalance with respect to the utilization of workers (i.e., decrease the high utilization of 95% of worker A and increase the utilization of the other workers). Assuming a fair distribution of work among the workers, each worker will be occupied 80% of the time. Figure 1.3 shows that all workers and machines are now chained through the worker skills. In terms of graph theory, the graph becomes connected, since the addition of skill B-II creates a path that directly or indirectly connects worker A with the other workers and machines.

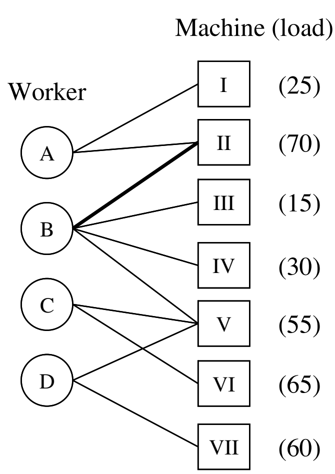

Figure 1.3 Additional training to enable an equal workload division.

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 intergroup conflicts, leading to the disintegration of a team (see Wilke and Meertens, 1994). Therefore, chaining is an important aspect to include in developing cross-training policies.

However, training worker B for machine II is only one possibility of realizing a chained cross-training configuration with a minimal number of additional cross trainings. Other possible additional cross trainings, which would create a chained graph, are B-I, C-I, C-II, D-I, and D-II. Several other considerations may play a role in selecting the best additional cross training.

1.2.2.3 Multifunctionality and redundancy

Molleman and Slomp (1999) define the flexibility of a labor system in more detail by giving three concepts. Functional flexibility may be defined as the total number of skills in a team. The other two concepts are *multifunctionality* and *redundancy*. The level of multifunctionality is defined as the number of different machines a worker is able to cope with, and redundancy (machine coverage) is defined as the number of operators that can operate a specific machine. In terms of graph theory, multifunctionality and redundancy are represented by the degrees of the vertices. The degree of a vertex is defined as the number of edge ends at that vertex. The degree of an operator vertex represents the multifunctionality of the operator and the degree of a machine vertex represents the redundancy of the machine. With respect to multifunctionality and redundancy, two issues should be addressed. First, setting minimum and/or maximum levels should be considered. Second, consideration should be given to the question of whether the level of multifunctionality/redundancy should be as equal as possible for all workers/machines or if some differentiation should be allowed.

Setting a maximum level of multifunctionality may be appropriate in production environments where learning additional tasks/machines requires extensive (and expensive) training and/or where forgetting aspects play a large role. Minimal levels may be appropriate in DRC systems with low staffing levels (ratio of workers to machines), frequent machine breakdowns, or (large) fluctuations in demand. Boundaries for multifunctionality may also be set individually. 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.

As for redundancy, 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. To what extent should multifunctionality and redundancy be bounded? A certain level of multifunctionality and machine coverage is needed in order to deal with fluctuations. When there is too much multifunctionality and machine coverage, worker skills may remain unused and workers may begin to feel that their contributions to team performance are less unique. In the illustrative example, we assume, for illustration purposes, that the minimal machine coverage is one.

Molleman and Slomp (1999) also concluded that an equal distribution of qualifications among workers creates the best situation to deal with absenteeism of workers. This can be explained by the fact that the absenteeism of highly multifunctional workers deteriorates the performance of a team much more than the absenteeism of less multifunctional workers. An equal distribution of qualifications reduces the negative effect of the absence of the workers with the highest level of multifunctionality. As a result of this consideration, the cross-training B-II is no longer ideal. It is better to cross train, for example, worker C for machine II (Figure 1.4).

This assignment is better with respect to the ability of a team to respond to absenteeism. An equal distribution of qualifications is also better from a social viewpoint, since it enhances feelings of interpersonal justice and equity within a team if workers help each other and share their workloads (e.g., Austin, 1977). The wish to gain an equal distribution of qualifications seems obvious from the viewpoint of the ability to deal with absenteeism and the social viewpoint. Most prior studies on DRC systems focus on single-level labor flexibility, in which workers receive the same degree of cross training and thus are equal in terms of multifunctionality. Little is known about the effects of unequal multifunctionality. An exception is a study by Felan and

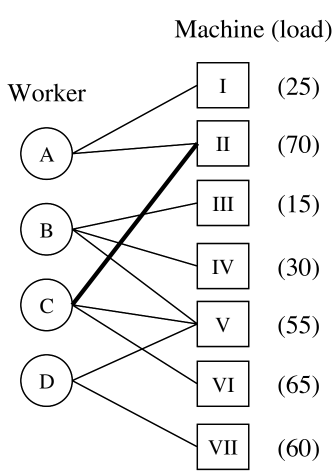

Figure 1.4 Additional skill to enable a more equal level of multifunctionality.

Fry (2001), who focus on multilevel 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 multifunctionality remain unclear and likely depend on the specific context. In a situation with absenteeism and without labor learning, for example, we expect equal multifunctionality to be the best option.

In the illustrative example of Figure 1.4, the choice of equalizing or not equalizing redundancy in a manufacturing team does not lead to a different cross-training outcome. Whether the level of redundancy 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, therefore, is 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.

1.2.2.4 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 draws attention to a worker's contribution to group performance (Clark, 1993). Cross training, therefore, may 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 (e.g., 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

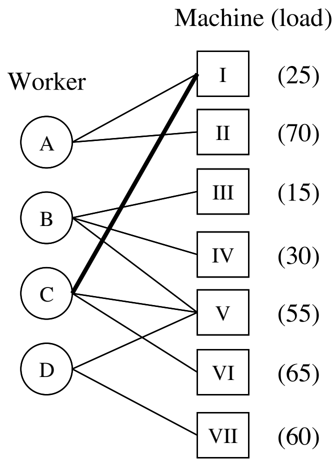

Figure 1.5 Adding a skill to minimize collective responsibility.

trainings should 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. 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. Figure 1.5 illustrates that this, in addition to the aspects considered before, leads to the situation that worker C needs to be trained for machine I instead of machine II.

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 nonobvious choice for managers in developing a cross-training policy.

An alternative for cross training worker C for machine I is to cross train worker D for machine I (Figure 1.6). This leads to a better division of worker responsibility (i.e., a more equal amount of (partially) shared workload per worker) and supports equity among workers.

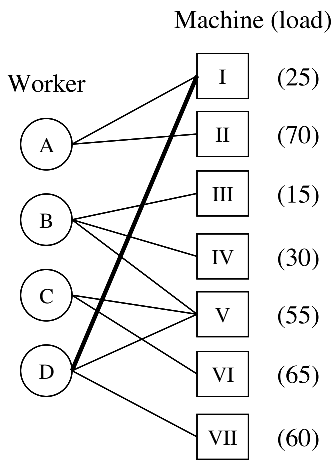

Figure 1.6 Adding a skill to enable a more equal worker responsibility.

1.2.3 *An IGP model and evaluation of specific cross-training policies*

1.2.3.1 *An IGP model to formalize cross-training policies*

The Integer Goal Programming (IGP) model presented in this section (see also Bokhorst et al., 2004b) formalizes various rules for specifying how important aspects should be addressed, and subsequently can be used to support the application of a cross-training policy. 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. Here, 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.

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. Table 1.2 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.

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. 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

Table 1.2 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 (IGP) Model

Aspect	Description (and alternative rules with aspects 3, 4, and 5)	Expression in the IGP model
1	Extent of cross-training Minimize the number of additional cross trainings.	First goal in the objective function; setting *AddCT* to zero in constraint (7)
2	Chaining Enable an equal workload division among the workers to encourage "chaining"	Constraint (3)
3	Multifunctionality Rule 1: Equal multifunctionality per worker Rule 2: Unequal multifunctionality 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 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

Source: Bokhorst J.A.C., Slomp J., and Molleman E., 2004, *IIE Transactions*, 36(10), 969–984. With permission.

the case, then there will be no subgroups under any of these circumstances or, in other words, there is always the possibility of chaining. Constraint (4) forces workers to be or become trained for the machines they must operate. Constraints (5) and (6) concern the minimum levels of multifunctionality and machine coverage, respectively. These two constraints indicate basic choices facing the manager responsible for cross training workers. Additional constraints concerning maximum levels of multifunctionality and machine coverage can be included easily, if necessary.

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 (AddCTs). 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 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.

The second goal of the objective function concerns balancing multifunctionality among workers by minimizing the maximal deviation ($d^{+}_{equalMF}$) from optimal multifunctionality. Constraint (8) calculates this deviation. Optimal multifunctionality 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.

Notation:
Index sets:

$\{i=1,\ldots,I\}$ = Index set of machines.

$\{j=1,\ldots,J\}$ = 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 multifunctionality.

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:

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

1.2.3.2 An evaluation of cross-training policies

As we have seen in Section 1.2.2, research has failed to provide unambiguous rules for addressing multifunctionality, 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, have considered eight alternative cross-training policies (Bokhorst et al., 2004b), based on two different choices that can be made with respect to each of the following aspects: multifunctionality, machine coverage, and collective responsibility (Table 1.3). Within each of these cross-training policies, the same rules are included to deal with the other aspects.

Table 1.3 Alternative Cross-Training Policies

Choices	Cross-training policies							
	I	II	III	IV	V	VI	VII	VIII
Equal multifunctionality	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

Source: Bokhorst J.A.C., Slomp J., and Molleman E., 2004, *IIE Transactions*, 36(10), 969–984. With permission.

Simple aggregated data from a generic manufacturing team is used for applying cross-training policies to create cross-training configurations. Information concerning the workloads of various machines and the current skill matrix of workers is used as a starting point.

Using the IGP model introduced in Section 1.2.3.1, we formally applied the eight cross-training policies of Table 1.3 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 5 workers). 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.

We evaluated the eight resulting cross-training configurations (Table 1.4) by means of a simulation study. We used mean flow time (MFT) from an operations management viewpoint and the standard deviation of the distribution of workload among workers ($SD_{workload}$) from a human resource management viewpoint. 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.

Further, three routing structures were examined as a contextual factor: a parallel routing structure, a serial routing structure, and a job shop routing structure. Within the parallel structure, each part-type visits 1 of the 10 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 1 and 10 machines, while the order of the routing steps is random. As a fixed contextual factor, short, temporary absenteeism (1 to 5 days) was modeled, since the consequences of this type of absence are much more disruptive than are those of medium, long-term, or planned absenteeism.

The results show (see Bokhorst et al., 2004b) that within the parallel structure, it is important for MFT that either multifunctionality 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 multifunctionality 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 (OM) and of Human Resource Management (HRM) 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.

Table 1.4 Eight Cross-Training Configurations

Machine (load)	I Worker W1	W2	W3	W4	W5	II Worker 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 Worker W1**	**W2**	**W3**	**W4**	**W5**	**IV Worker 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 Worker W1**	**W2**	**W3**	**W4**	**W5**	**VI Worker 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 Worker W1**	**W2**	**W3**	**W4**	**W5**	**VIII Worker 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

(continued)