Worker flexibility in dual resource constrained (DRC) shops

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CHAPTER 2

LITERATURE REVIEW AND EXPERIMENTAL DESIGN

The chapter is concerned with literature review and experimental design with respect to worker flexibility issues in a DRC parallel shop. Section 2.1 studies the production environment in which cross training takes place, and explores the factors that may have impact on cross training decisions. Section 2.2 reviews the literature related to worker flexibility in DRC systems, and in particular, focuses on two issues, the level of cross training, and the degree of chaining. Section 2.3 deals with experimental design.

2.1 Extension of Nelson's model

Nelson's model was developed for studying worker flexibility issues in DRC systems (Nelson 1967). It covers the major transformation procedures, and has been used as a basis by most of the later DRC studies. This section presents the framework of Nelson's model for a better understanding of worker flexibility issues in DRC systems, indicates its limitations with respect to environmental and human aspects, and extends Nelson's model by including parameters such as part type repetitions, learning and forgetting, and individual learning patterns.

2.1.1 Nelson's model

Nelson's model was introduced in 1967. It has been regarded as the first model in DRC research, and was later referred to by most DRC research. Though some modifications have been made by these later studies to suit their own purposes, the major framework of the model still remains the same. Since Nelson's model has provided a comprehensive overview of the main elements of a DRC system, we would like to present it in the beginning of this thesis. By studying Nelson's model, we would understand better how a real life DRC system has been simplified and simulated, in particular, what areas have been covered in the model, and what areas have been mostly simplified or neglected. We will also indicate what modifications or extensions have been made to Nelson's model by later research. This understanding may help us to identify the limitations of Nelson's model and the later modifications with respect to shop parameters, their settings, and their impact on system performance.

Nelson's model is depicted in Figure 2.1. It must be understood that our emphasis is only on the general structure of the model. In other words, we only like to understand the main components of the model, and the way they match elements of DRC systems in practice. We are not interested in a particular parameter, since we are not examining the relationships between any of these parameters in this section. Therefore, we will not discuss these parameters in detail.

Workload Parameters:

a(.) the job inter-arrival distribution density function.
λ the mean arrival rate of jobs into the system.
p_{ij} the job routing transition probability from machine center i to machine center j, (i = 1, 2, ---, m; j = 1, 2, ---, n).
s_i(.) the service time density function for each machine in machine center i, (i = 1, 2, ---, m).
u_i the mean service rate of each machine in machine center i, (i = 1, 2, ---, m).

Design Parameters:

m the number of machine centers in the system.
c_i the number of identical machines in machine center i, (i = 1, 2, ---, m).
n the number of workers in the workforce.
e_{ji} the relative efficiency of worker j on an machine in machine center i, (i = 1, 2, ---, m; j = 1, 2, ---, n).

Control Parameters:

l the machine center selection procedure used in central control.
q_i the queue discipline used at machine center i, (i = 1, 2, --- m).
d_i the degree of centralized worker assignment control exercised at machine center i, (i = 1, 2, ---, m).

Figure 2.1 Nelson's model (1967)

Nelson's model comprises three groups of parameters. The first group, workload parameters, consists of the frequency of job arrivals, the processing time, and the routing patterns of jobs. The second group, design parameters, encompasses the design issues such as cross training policies, the machine-staffing levels, the worker utilization levels, and the organizational size and structure. The third group, control parameters, pertains to how to operate a dual resource constrained system. Basically, there are three control rules: the job dispatching or queuing rule, and the "when" and the "where" worker assignment rules. The job dispatching rule specifies the queue discipline for jobs. The "when" rule determines the moment at which a worker is eligible for transfer to another machine, and the "where" rule selects a machine and assigns the eligible worker to that machine. These three groups of parameters, workload, design, and control, cover the main operating processes in a real life DRC system.

Though Nelson's model captures the major characteristics of a DRC system, it focuses mainly on control rules and design decisions. The purpose of this thesis is to study worker flexibility issues, which attempt to involve more dynamic and human aspects. Nelson's model may not suit this purpose in these two respects. In his model, the assumptions concerning the variations of the input into the system were rather simple, and centered on the job file. Three stochastic elements were selected in the job file: job arrival intervals, job routings, and job processing time. These three parameters reflect the fluctuations in workload among machine centres. We argue that there are other sources of input variations, such as the changes of part types, the replacement of machines, and worker attritions or absenteeism. These kinds of variations were not included in Nelson's model.

Later studies also mainly focused on the operating rules and design decisions. Consequently, not many extensions have been made in terms of involving more dynamic aspects, apart from basic job characteristics. Only worker attritions have been introduced as a dynamic factor by Malhotra et al. (1993), Kher et al. (1999), and Kher (2000). In addition, worker absenteeism was studied by Molleman and Slomp (1999) in an analytical model.

The other limitation lies in the human aspects. As shown by the design parameters in Figure 2.1, the assumptions concerning human characteristics were also rather simple. Only worker efficiency was included. Later, learning and forgetting were regarded as the causes for training costs, and were introduced into DRC models (Malhotra et al. 1993, Kher et al. 1999, and Kher 2000). The trigger for the learning and forgetting processes was worker attritions. None of the existing DRC studies regarded the introduction of new product as an environmental variable, and the impact of their related learning costs on system performance. Furthermore, the differences in learning characteristics between workers have not yet been considered.

To conclude, Nelson's model covers most of the basic elements in a DRC system, but it has limitations with respect to dynamic and human aspects. Though some modifications have been made by other studies along these two dimensions, further extension of the model might be desirable. The extended model may provide a wide platform for the exploration of worker flexibility issues in greater depth.

2.1.2 Environmental dynamics and worker flexibility

This section examines the relationship between environmental dynamics and worker flexibility. We first introduce the concept of environmental dynamics, after which we present relevant theories in organization theory and human resource management. After that, we present the relevant findings in DRC systems.

A system is defined to be a collection of entities, for instance, people and machines, that act and interact together toward the accomplishment of some logical ends (Schmidt and Taylor, 1970). Dynamics refer to continuous changes, activity or progress. Therefore, the term, environmental dynamics, refers to how often and to what extent the system entities' attributes change over time. Since the components of a DRC system are machines, workers, and products, environmental dynamics in this context may be specified as changes in anyone of these components with respect to their presence and behaviour. Examples of such changes include the replacement of machines, worker attritions or absenteeism, the introduction of new products or the fluctuations in demand.

The importance of environmental dynamics to worker flexibility decisions has been highlighted by theories in organization design and human resource management. It is proposed by organization design theory that environmental uncertainty (i.e. environmental dynamics in our study) is related to worker flexibility decisions. In particular, the law of "requisite variety" asserts that to manage variety in output characteristics successfully, an organization should have enough means to transform the input of information, materials and parts into the output it desires (Ashby, 1969). To incorporate this law into the context of a DRC system, this law states that the amount of worker flexibility must be contingent on the level of environmental uncertainty. Therefore, it is suggested that the need for worker flexibility should match the degree of environmental dynamics.

The relationship between environmental dynamics and worker flexibility is also stated in a demand-supply model in the field of human resource management (Molleman, 2000). In this model, the work to be done forms the demand side for worker flexibility, while the employees and other "resources" form the supply side of worker flexibility. It was proposed that the supply of worker flexibility might be contingent upon the demand for worker flexibility, which in turn is caused by the diversity in environmental demands. Therefore, the theory in human resource management also suggests the possible link between environmental dynamics and worker flexibility.

Though both theories in organization design and human resource management proposed a possible link between environmental dynamics and worker flexibility, to the best of our knowledge, the existing DRC research has paid only limited attention to this link. Malhotra et al. (1993), Kher et al. (1999), and Kher (2000) considered worker attritions as a dynamic factor in their studies. The results showed that the impact of worker attrition on system performance in an environment with high learning costs might be significant. Molleman and Slomp (1999) addressed worker absenteeism. They reported that absenteeism has a very negative impact on system performance. McCreery and Krajewski (1999) used product variety to represent environmental dynamics in their study. The results showed that cross training policies and worker deployment policies are related to product variety and task complexity of the assembly line. The new product introduction is one of the components of product variety in their study. Therefore, they did not directly measure the impact of new product introduction on system performance.

The introduction of new products has been regarded as an important competitive means by many firms. Due to rapid changes in technology and intensive competitions, product life cycles are getting shorter and new products are introduced to the market at higher frequencies in both high technology industries and industries not commonly regarded as high technology. For example, from 1964 to 1976, IBM introduced only two new families of mainframe computers within twelve years. However, in the next four years, IBM introduced four new families of computers. From 1972 to 1980, Hewlett-Packard introduced 23 new models of calculators to keep pace with rapidly changing technology (Fraker, 1984). While the first generation of typewriters dominated the market for 25 years, subsequent generations have had progressively shorter life cycles: 15, 7 and 5 years (Nevens et al., 1990). In the early 1980's, in response to the threat posed to its market share by Yamaha, Honda replaced or introduced 113 motorcycle models over a period of 18 months thereby shortening the product life cycles of many of its own and also its competitors' models (Stalk, 1988, and Swamidass, 1988). Similar evidence of the trend towards shorter product life cycles exists in the semiconductor and automobile industries (Santo and Wollard, 1988, and Taylor, 1990). The rapid introduction of new products may have a huge impact on the various aspects of operations management.

The introduction of new products may trigger learning processes and incur learning costs, and therefore, offset the benefits of cross training. In this way, it may affect worker flexibility decisions.

2.1.3 Learning and forgetting

In this section, we focus on the relationship between learning and forgetting and worker flexibility. The detailed information concerning learning and forgetting models is provided in Appendix.

Learning and forgetting have been addressed by a number of studies in DRC research (Malhotra et. al 1993, Wisner and Pearson 1993, Kher et al. 1999 and Kher 2000, McCreery and Krajewski 1999, and Stratman et al. 2004). These studies indicated that when workers are cross-trained, they incur learning and relearning costs, and therefore, negatively affect system performance. Here, learning costs refer to productivity losses, which occur during learning processes as workers are typically less efficient. Relearning costs incur when workers are interrupted during learning processes, they move back on the learning curve and have to restart learning.

Learning was first introduced to DRC research by Malhotra et. al (1993). Their results indicated that learning has a significant impact on system performance, and learning costs might affect cross training policies. When learning costs are high due to slow learning rates and high initial processing time, it might be better to train workers with no more than two skills.

Later, forgetting was also included in DRC research by a number of studies (Wisner and Pearson 1993, Kher et al. 1999 and Kher 2000). They reported that forgetting has a negative impact on system performance, and learning and forgetting costs might shape the degree to which worker flexibility is needed.

McCreery and Krajewski (1999) addressed the need to match work flexibility decisions to the learning and forgetting environment in an assembly line. Strateman et al. (2004) compared the learning and forgetting costs of permanent workers with that of temporary workers in an assembly line.

Although the detrimental effects of learning and forgetting on system performance have been well documented, the extent of their impact might not have been fully estimated. In previous DRC research, worker attritions were used as the dynamic factor triggering learning events. Or in other words, learning processes are triggered by personnel changes in a system. For example, when an experienced worker leaves, a new inexperienced worker joins the system. Only the new worker needs to be trained, and learning is process related. Therefore, the influence of learning and forgetting on system performance has only been estimated to a limited extent.

As stated in the previous section, the introduction of new products has an increasing impact on operations management, and has been selected as a contextual variable, which represents environmental dynamics. In this way, the magnitude of the impact of learning and forgetting may be better estimated.

2.1.4 Individual differences

This section examines how individual differences have been addressed in the studies concerning worker flexibility. We first review how individual differences have been considered in DRC research. Next, we present the results of an empirical study, which examines the individual differences in learning capability, and offers us an argument to include it in the DRC model in this thesis.

2.1.4.1 Worker efficiency levels

In DRC research, the individual differences among workers have been studied in a very limited fashion. Several studies (Nelson 1970, Hogg, Phillips and Maggard 1977, and Bobrowski and Park 1993) assumed a heterogeneous workforce, in which workers have different efficiency levels. In reality, workers may have received the same level of cross training, but due to the differences in intelligence, motivation, self-efficacy, and other factors, they may still end up with different levels of efficiency. Note that the focus of these studies was on worker assignment rules rather than cross training policies.

Nelson (1967) first included the individual differences in efficiency levels in his model. As shown in the design parameters of Figure 2.1, he used an indicator e_{ji}

to represent the efficiency of worker i at machine centre j. Consequently, the real processing time for a job will be determined by the estimated standard processing time, the specific worker (i), and the particular machine centre (j). By including an efficiency parameter in his model, Nelson highlighted the importance of human aspects in DRC research.

Later, Nelson (1970) further investigated the relationship between the differences in worker efficiency levels and the degree of centralized control. He showed that as the differences in worker efficiency levels increase, the importance of having more centralized control increases. This is because when the control of transfer is more centralized, workers have a higher possibility of being transferred to the department in which they are more efficient, and a lower possibility of being trapped in the department in which they are less efficient.

Hogg, Phillips and Maggard (1977) extended the work of Nelson (1970) by introducing three configurations, in which the differences in worker efficiency were attributed to workers, machines, and both workers and machines. They created worker assignment rules, which tried to incorporate efficiency information. The results showed that as the range of worker efficiencies increases, the impact of the worker assignment rules increases dramatically. Furthermore, they also discovered that the magnitude of the differences in performance between the various worker assignment rules is highly sensitive to the level of worker utilization. The differences in performance between the various worker assignment rules are relatively small at a low level of worker utilization, and relatively large at a high level of worker utilization. The reason is that the worker assignment rules used in their study are biased toward the more efficient workers. When the worker utilization level is high, worker assignment rules are triggered more frequently. As a result, workers will be more often assigned to the places where they have a higher efficiency level, instead of being trapped in the places where they have a lower efficiency level.

Bobrowski and Park (1993) created more worker assignment rules that incorporate worker efficiency information. Their results showed that in general these new rules outperform the traditional ones, which did not consider the differences in worker efficiency. Their findings are consistent with that of Hogg, Phillips and Maggard (1977). In addition, they indicated that when workers differ in efficiency, the "where" rules are more important than the "when" rules.

The foregoing suggests that the individual differences in general are important in worker flexibility decisions.

2.1.4.2 Learning capabilities

It is suggested by human resource management theory that workers may differ in learning capabilities. How much a worker can be trained will be affected by a worker's characteristics, such as intelligence and general mental ability (Molleman 2000). In addition, personality traits such as "self-efficacy (Bandura, 1993), which refers to the extent to which one believes that one is able to cope with a problem successfully, may also play a role. Since worker's learning capabilities differ, cross training policies that incorporate the individual differences in learning capabilities might have a potential to improve system performance.

The individual differences in learning capabilities have been confirmed in an industrial setting by Nembard and Uzumeri (2000). They selected two production facilities, one with manual tasks, and the other with procedural/cognitive tasks. The results indicate that regardless of whether the task is manual or procedural, fast learners learn fast but also tend to forget fast, while slow learners learn slowly but also are inclined to forget slowly. Furthermore, fast learners are associated with a lower final efficiency level, whereas slow learners are related to a higher final efficiency level. Therefore, workers have different learning patterns in terms of the learning and forgetting rates, as well as the final efficiency levels. Though in their study, why workers behave in this way was not explained, still their findings provide insights into the nature of individual learning processes, and are therefore included in our study.

The above arguments raise the first research question.

> What are the impact of part type repetitions and the individual learning patterns on system performance? In other words, how will the differences in performance between fast and slow learners vary with part type repetitions?

Summary

In section 2.1, we reviewed Nelson's model, and included three parameters: the part type repetition, learning and forgetting, and the individual differences in learning capabilities as the extension to a traditional model.

2.2 Cross training issues

This section addresses two research issues related to cross training policies: (1) the level of cross training, which concerns to what extent workers should be trained; and (2) the degree of chaining, which focuses on how workers' skills should be allocated.

2.2.1 Level of cross training

The level of cross training has been studied extensively in DRC studies (Treleven, 1989). It has been shown that increases in worker flexibility positively affect system performance (Allen 1963, Nelson 1967, Fryer 1973,1974, and 1976). Several studies also show a diminishing positive effect of a stepwise increase of the level of cross training (Park and Bobbrowski 1989, malhotra et al. 1993, Fry et al. 1995, and Molleman and Slomp 1999). Most of the positive effects can be achieved without going to the extreme of total flexibility.

It is believed that worker flexibility is accompanied with some extra costs. Malhotra et al. (1993) show that learning costs are positively related to the level of cross training, which in turn negatively affect system performance. In their study, learning costs were represented by two learning parameters, the initial processing time, and the learning rate, and learning processes were triggered by worker attritions. The results indicate that both learning parameters and worker attritions have a significant impact on the optimal level of cross training. Kher et al. (1999) and Kher (2000) extended the work of Malhotra et al. (1993) by involving forgetting, which brought the learning processes more close to reality. The results show that forgetting has a significant impact on system performance, and that in the presence of a high attrition and forgetting rate, a worker may not be able to achieve full efficiency for even two different types of machines.

As stated earlier, due to the increasing influence of new product introduction on operations management, we included part type repetitions, and learning and forgetting as parameters in the DRC model. We are interested in how part type repetitions affect the optimal level of cross training in a learning and forgetting environment. This raises the second research question:

> In a learning and forgetting environment, what is the impact of cross training and part type repetitions on system performance? In other words, will the impact of the performance of cross training vary with part type repetitions?

2.2.2 Degree of Chaining

The "chaining" concept was first introduced by Jordan and Graves (1995) to study process flexibility, which concerns the assignment of products to plants. The results show that limited flexibility, if chained properly, achieves most of the benefits in sales and plant utilization of total flexibility, and that it is better to chain products and plants to the greatest extent, or in other words, a long chain outperforms several short ones. However, Jordan and Graves (1995) only demonstrated the benefits of chaining, but did not consider any possible negative consequences such as setup time.

Later, several papers studied the chaining concept in various other contexts. Sheikhzadeh et al. (1998) applied the concept of chaining to manufacturing flexibility, which concerns the assignment of part types to machines. Their results are consistent with the findings of Jordan and Graves. In addition, they show that the desirability of limited flexibility over total flexibility is positively related to setup time. Their results indicate that chaining may have possible negative consequences such as setup time, which occurs each time a machine switches from one part type to another and tools, fixtures, or part programs have to be changed. The frequency of setups is determined by how many parts share the same machine and the scheduling policy used to sequence these parts on the machine. On the one hand, chaining positively affects system performance. When demand fluctuations occur at any individual plant in the chain, all the plants within a chain will be involved in responding to these fluctuations. This in turn leads to an increase in the magnitude of flexibility, and results in an improvement in performance. On the other hand, chaining may cause more frequently switches of product types for a given plant. This may lead to an increase in setup time, and therefore, negatively affect system performance. Their study highlighted the importance of considering the negative consequences of chaining when apply the chaining concept in a specific situation.

The chaining concept has also been applied to worker flexibility, which concerns the assignment of workers to machines. Brusco and Johns (1998), and Slomp and Molleman (2002) confirmed the advantages of chaining in the formation of cross training configurations.

The foregoing suggests that chaining is a generally useful principle for the design of a flexible structure, and it may hold for various contexts. However, in a DRC system with the presence of learning and forgetting, how chaining performs is still not clear and needs further investigation. This leads to the third question.

> What is the impact of chaining and part type repetitions on system performance when learning and forgetting are present? In other words, will the impact of the performance of chaining vary with part type repetitions?

2.3 Experimental design

This section discusses the design of the experiments for answering the research questions addressed earlier in sections 2.1 and 2.2. For ease of reading, they are listed below.

Research question 1

> What are the impact of part type repetitions and the individual learning patterns on system performance? In other words, how will the differences in performance between fast and slow learners vary with part type repetitions?

Research question 2

> In a learning and forgetting environment, what is the impact of cross training and part type repetitions on system performance? In other words, will the impact of the performance of cross training vary with part type repetitions?

Research question 3

> What is the impact of chaining and part type repetitions on system performance when learning and forgetting are present? In other words, will the impact of the performance of chaining vary with part type repetitions?

This section is organized as follows. Section 2.3.1 deals with experimental design. Section 2.3.2 discusses the simulation model. Section 2.3.3 explains the performance indicators.

2.3.1 Experimental factors

Three experiments are conducted to examine research questions 1, 2, and 3, respectively. Table 2.1 shows these three experiments and the experimental factors within each experiment.

2.3.1.1 Number of part type repetitions

The number of part type repetitions is modelled as an experimental factor, to capture the impact of the introduction of new part types on system performance. It refers to the number of lots that are to be produced for a specific part type before it is replaced by a new part type. In fact, it represents the product life cycle that a part type experiences in terms of product units, instead of time units.

Table 2.1 Three experiments with their experimental factors and levels

Exp	Experimental factor	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6
1	Number of part type repetitions	1	4	16	64	256	512
	Composition of the workforce	Fast learners	Slow learners				
	Cross training policies	I					
2	Number of part type repetitions	1	4	16	64	256	512
	Composition of the workforce	Slow learners					
	Cross training policies	II	III	IV			
3	Number of part type repetitions	1	4	16	64	256	512
	Composition of the workforce	Slow learners					
	Cross training policies	II	V				

To reflect various scenarios of new product introduction, six levels of part type repetitions are selected in our study: 1, 4, 16, 64, 256, and 512. These levels are based on the learning and forgetting model used in this study, which is presented in Appendix. In this model, when there are no interruptions, a slow worker (learning and forgetting rates 85%) will reach the plateau of his curve at 360 units. These six levels of part type repetitions distribute along this learning curve from the very beginning to the end. Although there are many other possible choices, the 6 levels selected here represent a wide range of environmental dynamics. For example, part type repetition 1 captures a highly dynamic situation, which part type repetitions 512 depicts a relatively stable situation. The remaining 4 levels represent moderate degrees of environmental dynamics between these two extremes.

2.3.1.2 Composition of a flexible workforce—fast or slow learners

For experiment 1, we assume that there are either fast or slow learners in the system. For the rest of the experiments, we assume that there are only slow learners in the system.

2.3.1.3 Cross training policies

5 cross training configurations are created for studying research questions 1, 2, and 3 (see table 2.2).

Table 2.2 Cross training configurations

Worker	I				II				III			
	Department				Department				Department			
	D1	D2	D3	D4	D1	D2	D3	D4	D1	D2	D3	D4
W1	1				1	1			1	1	1	
W2		1				1	1			1	1	1
W3			1				1	1	1		1	1
W4				1			1	1	1	1		1

Worker	IV				V			
	Department				Department			
	D1	D2	D3	D4	D1	D2	D3	D4
W1	1	1	1	1	1	1		
W2	1	1	1	1	1	1		
W3	1	1	1	1			1	1
W4	1	1	1	1			1	1

In cross training configuration I, each worker is trained for only one department. This configuration is designed for research question 1. It demonstrates how a DRC parallel shop performs in a situation, when workers learn and forget, and new products come into the system at various frequencies. Cross training configuration II, III, and VI are used to examine to what extent workers should be cross-trained, i.e. research question 2. In these configurations, workers are trained for two, three, and four skills, respectively, and due to the benefits of chaining, the allocation of worker skills forms a long chain. In configuration V, workers are trained for two skills, but form two short chains. Configurations II and V have the same level of cross training, but workers are allocated in different ways. By comparing their performance, we will know how chaining performs in a learning and forgetting environment with the introduction of new products, i.e. research question 3.

2.3.2 Simulation model

This section specifies the fixed parameters that comprise the simulation model in our study.

The DRC parallel shop consists of four departments, each with two identical machines. There are four workers in the parallel shop. The 50% staffing level in this study falls into the optimal range between 50% and 75%, as proposed by other studies (Rochette and Sadowski, 1976, and Treleven and Elvers, 1985). Workers may have different learning and forgetting rates. Fast learners have learning and forgetting rates 85% and 85%, while slow learners 80% and 80%. Fast learners have a lower final efficiency level, by which the final processing time reduces to 50% of the initial processing time. Slow learners have a higher final efficiency level, by which the final processing time decreases to 25% of the initial processing time. The specific composition of the workforce varies across experiments. The details regarding the learning and forgetting model can be found in Appendix.

The job file of a classical DRC model comprises three parameters: job arrival rates, job processing time, and job processing routings. Besides, we create a part type file to reflect the procedure of new part type introduction (see Figure 2.2).

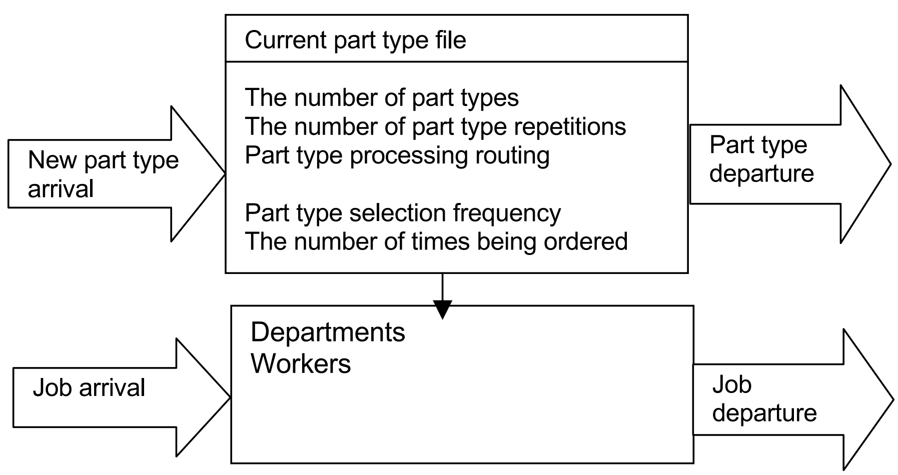

Figure 2.2 A Parallel shop model with the introduction of new part types

It includes a number of parameters, namely (1) the number of part types, (2) the number of part type repetitions, (3) the part type processing routing, (4) the part type selection frequency, and (5) the number of times being ordered.

The number of part types being presented simultaneously in the model is assumed to be finite, i.e. 40 part types. Since in reality few shops have a truly infinite product range, this assumption brings our model closer to the real life situation. Felan and Fry (2001) also used a finite number of products in their model. To keep the number of part types constant, we assumed a replacement policy for the introduction process of new part types. In particular, once a part type reaches the end of its life cycle, i.e. being produced for a predetermined number of times, it is deleted from the part type file, and at the same time, a new part type is added. A replacement policy might be applied to situations, in which managers are concerned with the learning and relearning costs that may result from the introduction of new part types, and thus prefer to keep a limited number of part types. McCreery and Krajewski (1999) also used a limited product file, with the number of part types ranging from 5 to 10, and with a part type replacement rate from 25% to 50% per year.

The number of part type repetitions is generated from a uniform distribution. With respect to part type processing routing, we assumed that each part type will be processed only in one department, and then it leaves the system. Once a new part type arrives, it is assigned to one of the four departments randomly. Finally, each part type has an equal chance of being selected by a customer order. For example, when the number of part types in the parallel shop is 40, each part type has 2.5% (1/40) opportunities of being selected. Once a part type is selected, the times of being ordered is recorded in the part type file.

A number of operating policies are needed in order to run a DRC parallel shop. These policies include: when a worker is available to transfer; when more than one worker is available, which one should be selected; where should the selected worker be assign to; and how jobs are dispatched to departments. These policies are referred to as the 'when' rule, the 'who' rule, the 'where' rule, and the job dispatching rule, respectively.

With respect to the 'when' rule, it has been noted that the decentralized control, in which a worker is eligible for transfer when he has finished all the jobs in queue, performs well when transfers take time, (Nelson 1967, and Malhotra et al., 1993), and therefore, is used here.

Bokhorst et al. (2003) indicated that the 'who' rule does not have a significant impact on system performance in case of realistic worker utilization. However, we choose the longest-idle-time as the 'who rule', which assigns the worker who has been idle the longest time when more workers are available. This rule attempts to equalize the workloads of workers, and was used in industrial practice and previous literature (Rochette and Sadowski 1976).

Compared to the 'when' rule, the 'where' rule have relatively little impact, noted in the previous literature (Fryer, 1973, Treleven and Elvers, 1985, and Weeks and Fryer, 1976). In our research, the 'longest queue' rule was selected. When a worker becomes eligible for transfer, the worker will be sent to the machine that has the most jobs in queue. This rule is widely applied in practice (Wisner and Siferd 1995). Besides, this rule has been shown to perform as well as other 'where' rules (Huang et al. 1984, Weeks and Fryer 1976, Russell and Taylor 1985, Treleven and Elvers 1985).

The impact of the job-dispatching rule, used to sequence jobs processing, is relatively unimportant (Park 1991). In our study, we chose the FCFS (First Come First Serve).

Job processing time was generated by using a negative exponential distribution. Here, the job processing time implies the size of order, which may be different each time for the same product type. The job arrival interval and the job processing time were selected so as to yield 85% worker utilization rate, when there are no learning and forgetting (i.e. the real processing times will not decrease with the accumulation of worker experience.). A 85% utilization is consistent with literature, as well as with industrial practice (Hogg et al. 1977, and Malhotra et al. 1993).

Worker utilization will go down in a learning and forgetting environment. This means when there are learning and forgetting, the worker utilization level realized in our experiments might be lower than that in a real life situation. We are that though the magnitude of the differences in performance between various cross training policies might be affected by lower levers of worker utilization, the rankings of the policies will affected according to Hogg et al. 1977). Noted that the operating rules in our study are chosen independently from worker utilization. All the relevant parameters used to model the parallel shop are summarized below in Table 2.3.

Table 2.3 Parameters in the parallel shop design

Parameters	Settings
Number of departments	4 (each department with 2 identical machines)
Number of workers	4 (They may have different learning and forgetting rates. The specific composition of fast and slow learners varies across experiments.)
Fast learners	Learning and forgetting rates 80% and 80% Final processing time equals 50% of the initial processing time
Slow learners	Learning and forgetting rates 85% and 85% Final processing time equals 25% of the initial processing time
Job arrival rates	Negative exponential distribution
When rule	Decentralized control
Who rule	Longest idle time
Where rule	Longest queue
Dispatching rule	First come first serve
Worker utilization	85%, when there are no learning and forgetting
Staffing level	50% (4 workers, and 8 machines)
Transfer time	15 time units

2.3.3 Performance criteria

Two types of performance criteria are selected: (1) mean flow time (MFT), and (2) worker utilization (UT). The mean flow time measures productivity, and has been widely used in DRC research (Nelson 1967, Fryer 1973, 1974, Weeks and Fryer 1976, Gunther 1979, and Malhotra et al. 1993). It is the average time that jobs spend in the system from arrival to completion, which includes processing time and waiting time for all jobs.

Worker utilization is computed as the total time that a worker is busy during a simulation divided by the total simulation time. It indicates how busy workers are involved with production activities on the shop floor.

$$UT = \frac{\sum_{i=1}^{N} \text{Busy Time of Worker i}}{\text{N x (Total Simulation Time)}}$$

where N is the number of departments where a worker can work at.

2.4 Summary of Chapter 2

The first part of this chapter dealt with literature review. We first studied Nelson's model, and discussed its limitations with respect to environmental uncertainties and human aspects. We then extended the traditional DRC model by including three parameters, environmental dynamics, learning and forgetting, and individual learning patterns. In this extended model, we addressed two worker flexibility issues, the level of cross training, and the degree of chaining, and reviewed the relevant literature. As a result, three research questions were raised.

In the second part of this chapter, we operationalized three experimental factors, the number of part type repetitions, the composition of a flexible workforce, and cross training policies, and presented an experimental design. After that, we introduced a simulation model, and selected a number of performance indicators.