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**“An Investigation into the Effectiveness of Bottleneck Based Input
Control Compared to Aggregate Input Control”**

by

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Abstract

The objective of this thesis is to gain a deeper insight into two different order release strategies used in production control systems. The first strategy puts a hold on the incoming jobs if the total workload on the shop floor exceeds a given trigger level. The second strategy allows or postpones the release of jobs onto the shop floor on the basis of the Work En Route to the bottleneck machines. The relative performance and complexity of these two order release strategies are important in achieving successful reduction in work-in-process inventory and in maintaining reasonable leadtimes.

First, a review of the literature on shop floor control and, more specifically, on release systems is provided. Next, a spreadsheet analytical model is developed to study the characteristics of each strategy. Then an experimental model is built using discrete-event simulation to provide more understanding of the effectiveness of each strategy. Finally, statistical analyses of the results are carried out to compare the performances of both strategies.

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Table of Contents

Approval page.....	ii
Abstract.....	iii
Acknowledgements.....	iv
Dedication	v
Table of Contents.....	vi
List of tables.....	xii
List of figures.....	xiv
List of abbreviations	xvi
1. Introduction.....	1
2. Production control methods	6
2.1. Definitions.....	7
2.1.1. Production facility.....	7
2.1.1.1 Some well known shops.....	9
2.1.2. Job Characteristics	9
2.1.3. Performance measures	10
2.2. Order Review/Release	11
2.3. From the Optimized Production Technology (OPT) to the Theory Of Constraints (TOC).....	22
2.3.1. Optimized Production Technology (OPT).....	22
2.3.2. Theory Of Constraints (TOC).....	24

2.3.3. Studies relevant to TOC.....	27
2.4. Job sequencing.....	28
2.5. Research goal	31
3. Experimental framework	33
3.1. General model description	33
3.2. Bottleneck machine.....	38
3.3. Release strategies	38
3.3.1. The Maximum Hours Strategy (MH)	39
3.3.2. Bottleneck Input Control (BIC) strategy.....	40
3.4. The bottleneck priority rule (BNPR)	41
3.5. Comparison of the strategies.....	41
4. Queuing model.....	42
4.1. General assumptions	42
4.2. Formulas development.....	43
4.3. Incorporation of the two release strategies	46
4.4. Model parameters.....	48
4.5. A spreadsheet implementation	49
4.5.1. The EXCEL spreadsheet.....	50
4.5.2. The transition matrix.....	52
4.6. Analytical Results	54
4.6.1. The flowshop	55
4.6.2. The jobshop.....	58

4.6.3. Comparison of the two shops.....	60
4.6.4. Conclusion	60
5. SIMAN model.....	62
5.1. Summary of the model file	62
5.1.1. Model parameters [10].....	63
5.1.2. Random Numbers [12].....	64
5.1.3. Creation of a new job [1], [3]	64
5.1.4. Flowshop model [2]	65
5.1.5. Release of the job to the shop [4].....	65
5.1.6. Arrival of jobs to machines [5], [6], [8].....	65
5.1.7. Management of the queues [7].....	66
5.1.8. Collection of statistics [9], [9A]	66
5.2. Validation of the model	67
6. The production environment.....	68
6.1. Parameter selection	68
6.2. Experimental plan	70
6.2.1. Experimental factors	70
6.2.1.1 Due date settings	73
6.3. Data collection	73
6.3.1. Variance reduction technique	74
6.3.2. Warm-up period	75
6.3.3. Run length.....	75

6.3.4. Number of replications	76
7. Selection of Order Release Parameters.....	78
7.1. Operating curves	78
7.1.1. Preliminaries	79
7.1.2. Simulation warm-up and run length	80
7.1.3. Creation of the curves	81
7.1.4. Comments on the operating curves.....	82
7.1.4.1 The flowshop model	83
7.1.4.2 The jobshop model.....	87
7.1.4.3 Comparison of the two shops.....	90
7.2. Trigger level selection.....	92
8. Analysis of Results	95
8.1. Notation.....	96
8.2. Assumptions underlying the ANOVA.....	96
8.2.1. The flowshop	97
8.2.2. The jobshop.....	100
8.2.3. Summary	102
8.3. Results for the throughput, the WIP and the leadtime	103
8.3.1. The flowshop	103
8.3.1.1 The throughput.....	104
8.3.1.2 The WIP	105
8.3.1.3 The leadtime.....	108

8.3.1.4 Summary	113
8.3.2. The jobshop.....	114
8.3.2.1 The throughput.....	114
8.3.2.2 The WIP	116
8.3.2.3 The leadtime.....	118
8.3.2.4 Summary	121
8.4. Tardiness measures	122
8.4.1. The flowshop	123
8.4.2. The jobshop.....	131
8.4.3. Summary	136
8.5. Discussion	137
9. Conclusions and further research.....	141
9.1. Summary of the research	141
9.2. Further research	142
Bibliography	144
Appendix 1. Queuing model results for the flowshop	151
Appendix 2. Queuing model results for the jobshop	164
SIMAN Model	169
Appendix 3. SIMAN experiment file	173
Appendix 4. Moving average of the worst case scenarios.....	176
Appendix 5. Correlograms for the worst case scenarios	178
Appendix 6. Operating curves for the flowshop.....	180

Appendix 7. Operating curves for the jobshop	192
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List of tables

Table 1: List of dispatch rules.....	37
Table 2: List of the possible routings for the flowshop	49
Table 3: Transfer matrix for the flowshop, with the MH strategy.....	52
Table 4: Example of the transition matrix for the jobshop	53
Table 5: Times in the flowshop	55
Table 6: Coefficients of variation of the interarrival times for the flowshop	58
Table 7: Times in the jobshop.....	59
Table 8: Coefficients of variation of the interarrival times in the jobshop	60
Table 9: Model parameters	63
Table 10: Experimental factors	71
Table 11: Trigger levels used to determine the warm-up period and the run length	81
Table 12: Trigger levels (in hours) chosen for the different settings for the ANOVA.....	94
Table 13: Experimental factors	95
Table 14 : Results summary table for the flowshop	104
Table 15: ANOVA for the throughput in the flowshop	105
Table 16: ANOVA for the WIP in the flowshop	108
Table 17: ANOVA for the leadtime in the flowshop.....	113
Table 18: Result summary table for the jobshop	115
Table 19: ANOVA for the throughput in the jobshop	115
Table 20: ANOVA for the WIP in the jobshop	118

Table 21: ANOVA for the leadtime in the jobshop.....	122
Table 22: Results aggregated over the dispatch rules for the jobshop.....	122
Table 23: Results summary table for MT in the flowshop	124
Table 24: Results summary table for TD in the flowshop.....	125
Table 25: ANOVA for MT3 in the flowshop	129
Table 26: ANOVA for MT6 in the flowshop	129
Table 27: ANOVA for TD3 in the flowshop.....	130
Table 28: ANOVA for TD6 in the flowshop.....	130
Table 29: Results summary table for MT in the jobshop.....	131
Table 30: Results summary table for TD in the jobshop	132
Table 31: ANOVA for MT6 in the jobshop.....	135
Table 32: ANOVA for TD6 in the jobshop	136

List of figures

Figure 1: Scheme of a production plant.....	8
Figure 2: Example of the Excel spreadsheet.....	50
Figure 3: Times in the flowshop when dummy machine processing time is 0.2.....	56
Figure 4: Times in the flowshop when dummy machine processing time is 0.85.....	57
Figure 5: Operating Curve for balanced flowshop, no BNPR, FCFS.....	82
Figure 6: Operating curve for a flowshop with a light b/n, no BNPR, FCFS.....	84
Figure 7: Operating curve for a flowshop with severe b/n, no BNPR, FCFS.....	85
Figure 8: Operating curve for a balanced flowshop, BNPR and FCFS	86
Figure 9: Operating curve for a balanced flowshop with no BNPR and SPTT	87
Figure 10: Operating curve for a balanced flowshop with BNPR and SPTT	87
Figure 11: Operating curve for a balanced jobshop with no BNPR and FCFS	88
Figure 12: Operating curve for a jobshop with a light b/n, no BNPR and FCFS	89
Figure 13: Operating curve for a jobshop with a severe b/n, no BNPR and FCFS	89
Figure 14: Operating curve for a jobshop with severe b/n, BNPR and FCFS	90
Figure 15: Scheme explaining the choice of the trigger levels.....	93
Figure 16: Example of a Normal Probability plot	98
Figure 17: Residuals against fitted values for the throughput in the flowshop	98
Figure 18: Residuals against fitted values for the WIP in the flowshop.....	99
Figure 19: Residuals against fitted values for the leadtime in the flowshop	99
Figure 20: Residuals against fitted values for the throughput in the jobshop.....	100

Figure 21: Residuals against fitted values for the WIP in the jobshop	101
Figure 22: Residuals against fitted values for the leadtime in the jobshop	103
Figure 23: WIP in the flowshop without BNPR	106
Figure 24: WIP in the flowshop with BNPR	106
Figure 25: Leadtimes in the flowshop without BNPR.....	110
Figure 26: Leadtimes in the flowshop with BNPR.....	110
Figure 27: WIP in the jobshop without BNPR	117
Figure 28: WIP in the jobshop with BNPR	117
Figure 29: Leadtime in the jobshop without BNPR.....	120
Figure 30: Leadtime in the jobshop with BNPR.....	120
Figure 31: Mean tardiness (MT1, MT4) in the flowshop without BNPR	126
Figure 32: Mean tardiness (MT1, MT4) in the flowshop with BNPR.....	126
Figure 33: Percentage of tardy jobs (TD1, TD4) in the flowshop without BNPR	127
Figure 34: Percentage of tardy jobs (TD1, TD4) in the flowshop with BNPR	127
Figure 35: Mean Tardiness (MT1, MT4) in the jobshop without BNPR	133
Figure 36: Mean tardiness (MT1, MT4) in the jobshop with BNsPR	133
Figure 37: Percentage of tardy jobs (TD4, TD1) in the jobshop without BNPR.....	134
Figure 38: Percentage of tardy jobs (TD1, TD4) in the jobshop with BNPR.....	134

List of abbreviations

ANOVA	Analysis of Variance
B/N or b/n	Bottleneck
BIC	Bottleneck Input Control
BNPR	Bottleneck Priority Rule
CONWIP	Constant Work-In-Process
CR	Critical Ratio
CRN	Common Random Numbers
DBR	Drum-Buffer-Rope
DI/OCS	Dynamic Input/Output Control System
DSOP	Dynamic Slack per Operation
EDD	Earliest Due Date
FCFS	First Come First Served
FIFO	First In First Out
I/O	Input/Output
JIT	Just-In-Time
LPT	Longest Processing Time
MH	Maximum Hours
MIL	Modified Infinite Loading
MILP	Mixed Integer Linear Programming

MRP	Material Requirement Planning
MT	Mean Tardiness
NOP	Number of Operations
OCR	Operation Critical ratio
ODD	Operation Due Date
OPT	Optimized Production Technology
OR	Order release
ORR	Order Review/Release
PPW	Processing Plus Waiting time
RS	Release Strategy
SCR	Smallest Critical Ratio
SFC	Shop Floor Control
SPO	Slack Per Operation
SPT	Shortest Processing Time
SPTT	Shortest Processing Time Truncated
TD	Percentage of tardy jobs
TOC	Theory Of Constraints
TWK	Total Work Content
WIP	Work-In-Process

1. Introduction

Companies are facing increasing competition due to the globalization of markets. Nowadays it is no longer sufficient to produce a high quality product. Other key elements are also essential for the success of a firm. Since technology is evolving very quickly, changes in production tools and in demand patterns become more and more frequent. To remain at the top, a company must be able to respond to these changes effectively. In particular, the production process, which is the heart of any manufacturing company, must be carefully planned and controlled. The following two issues are often considered as critical:

1. The time required by a company to satisfy a given demand is often critical to obtain customer orders. This time must be relatively short to accommodate changes in both the design of products and the volume demanded. It must also be predictable to ensure high delivery performance reliability.
2. All forms of inventory, including work-in-process inventory (WIP), contribute significantly to production costs. Historically a large inventory has been considered an asset. However, recently there has been increased recognition that excessive inventory ties up capital unnecessarily and makes response to changes in demand or product designs more difficult.

As a consequence, a lot of research has focused on production control over the last thirty years. The Reorder Point System was one of the first tools used to control inventory. In this system, every time inventory falls to a critical level, a fixed quantity of the component or product is ordered. This system has the advantage to be very easy to implement and to control. However, it does not coordinate dependent demands. It is therefore adequate only for very simple or highly repetitive environments.

Material Requirement Planning (MRP) was the first production planning system to explicitly recognize demand dependencies when determining material requirements. Given a requirement date, the leadtimes and the Bill Of Materials for any item, MRP uses backward scheduling to determine the timing needs for raw materials and the required starting dates for production. MRP is useful inasmuch as it facilitates coordination of parts going into assemblies, commonality of parts across assemblies and batch sizing. MRP is often classified as a push system. In such systems, the release date is established by subtracting a planned leadtime from the customer due date. Once processing is started, the material is pushed between stations: upon completion of a stage, the material goes immediately to the next one. Note that MRP assumes that the leadtimes are constant. Moreover, MRP is unable to shift release dates if capacity problems occur. Unfortunately, the infeasibility of the plans generated by MRP is often not detected early enough.

With increased global competition during the 1970's and 1980's, Just-In-Time (JIT) received substantial attention among production managers. JIT is perhaps as much a production management philosophy as a production planning and control method. It

strives to eliminate all waste, which means basically anything that does not add value to a product. The JIT philosophy often implies a change in the culture of the company's workforce. Continuous improvement becomes the task of all and workers are often considered a good source of suggestions. Mutual respect and support between employees, workers and suppliers is therefore an asset.

WIP is considered as evil in JIT if it exceeds the amount necessary to maintain smooth production flows. Excessive WIP often hides problems by trying to compensate for inadequate procedures. The goal of JIT is to solve all problems, which tend to produce excessive inventory. Reduction in the set up times means lower batch sizes, ideally of size one, can be justified. Reduction in demand, processing time and other forms of variability means buffer inventories can be reduced. Improvements and simplifications of the manufacturing process also help in reducing WIP. Finally, high quality and reliability are essential to prevent defects and produce low cost products.

Kanban (Fogarty, Blackstone and Hoffmann, 1991) is the production control system associated with JIT. Unlike a push system, the parts are not transferred to the next operation before they are requested. Such a system is called a pull system, since the inventory is pulled downstream through every stage of production. Although the principles of JIT can be applied to most types of production, the Kanban system itself is most applicable to repetitive manufacturing with stable demand.

More recently, a production control approach advocated by the Theory of Constraints (TOC) has had an impact. TOC is based on the idea that only a few resources in the production facility substantially restrict the potential throughput. These resources

are called the constraints. TOC advocates controlling the queue in front of the constraints so that random problems at other resources do not prevent the constraints from working. Large queues at other machines are not necessary since they provide no benefits and only cause an increase in both leadtimes and work-in-process inventory. Like JIT, TOC tries to reduce inventory. However, TOC considers that production systems will never be completely balanced and that constraints will always exist. While these constraints should be eliminated where possible, it is beneficial to manage them properly until problems can be resolved. This is considered to be an ongoing cycle.

Besides these important systems, many researchers have recognized the importance of controlling production by the use of input/output control. Wight (1970) and Belt (1978) have been among the first to emphasize the importance of input control, or orders review and/or release (ORR). Order review consists of checking the incoming orders and determining if production capacity exists for timely completion. In this phase, some of the orders can be rejected. Order release, also referred to as input control, controls the release of accepted orders to the production floor. It prevents the production floor from becoming overloaded. As a consequence, the work-in-process inventory is kept reasonable and the time necessary for production is more predictable.

Most of the order release mechanisms are designed to control the total workload in the shop. More recently, there has been an interest in ORR systems that control only the workflow to busiest machines in the shop. In this thesis comparisons are made between these two input control methods by means of simulation and analytical models.

The first method limits the total WIP in the production system whereas the second one regulates the queues in front of the busiest machines.

In the next chapter, the principal approaches developed for input control are summarized. The objectives of this research are presented at the end of that chapter. In chapter 3 the general framework for this research is presented. Chapter 4 is devoted to the development and analysis of an analytical model. The simulation model is described in chapter 5. In chapter 6 the choice of parameters for the model is explained, and the experimental plan is defined. In chapter 7 some preliminary analysis is provided. In the second part, the details of the simulations are given. In chapter 8 the results are statistically analyzed and discussed. A summary of the results and some ideas for further research are given in the last chapter.

2. Production control methods

In the 1970's many production facilities did not have any input control and orders were usually released on the shop floor immediately. When there is no control of the input of a shop, queues may build up if relatively many orders are already present on the shop floor. This is particularly true when the variation in processing times is high. A simple example of queuing theory illustrates this fact. Consider a Jackson Network queuing system where interarrival and service times are negative exponential. Then the interarrival time at every machine is negative exponential and the expected number of parts waiting at each resource is given by $\rho^2/(1-\rho)$, where ρ is defined as the machine utilization. Therefore the queues grow with the machine utilization. Moreover, the queues grow to infinity as the utilization of any machine approaches 100 percent. Under heavy, unregulated work loading it is difficult to predict the behavior of such things as job flowtimes. The longest queues naturally appear in front of the most utilized machines, called bottlenecks or constraints.

In order to prevent the queues from growing excessively, several input control methods have been considered in manufacturing companies over the last two decades. They all respond to the need for firms to use their resources more effectively, to reduce the variation in leadtime and to eliminate waste. In this chapter, several of these methods are discussed. Sections 2.2 and 2.4 present the theoretical background while section 2.3

focuses on ideas advocated in the Theory Of Constraints (TOC). For the sake of clarity, definitions that will be used throughout the text are provided first.

2.1. Definitions

2.1.1. Production facility

Shop floor. Where the transformation of orders from raw materials to finished goods takes place.

Balanced shop. A shop where all the machines have the same utilization.

Unbalanced shop. A shop where not all the machines have the same utilization.

Resources or machines. The equipment, the tools, the manpower, etc. necessary for production.

Bottleneck. A resource that has the highest, or one of the highest, utilization, and therefore restricts the throughput potential of the shop.

Non-bottleneck. A resource that is not a constraint.

Constraint. Anything that prevents a company from achieving better performance.
A constraint can be the result of a limited resource.

Jobs. Units of a product to be processed on the machines.

Orders. The requirements specifications for an incoming job.

Workload (at a machine). All the work waiting to be processed at a particular machine, including the work currently loaded on the machine.

Aggregate Workload or Shop Load. This term is used to designate all the work released onto the shop floor that is not yet completed.

Work-In-Process (WIP). Amount of work on the shop floor. In this study, WIP is computed as the sum of the remaining processing time required for all the jobs on the shop floor.

Transfer batch. The number of units that are transferred together from one resource to another.

Process batch. The number of identical units that are processed in a row at a particular machine.

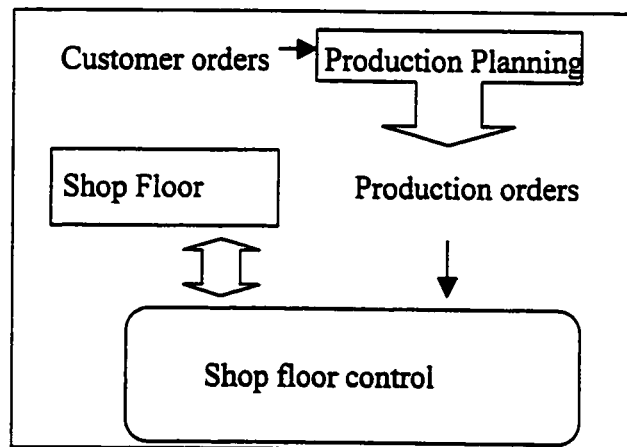


Figure 1: Scheme of a production plant

Several departments comprise a production plant (see Figure 1). For the needs of this thesis, it is considered that the planning department receives customer orders, and defines the production requirements. The production orders are then passed on to the shop floor control department for processing. This department is in charge of order release (OR).

2.1.1.1 *Some well known shops*

Research studies are often carried out for particular shop structures. The more common categories (Hax and Candea, 1984) are presented here.

In a *flowshop*, all the jobs are processed in the same order on the different machines. The flow is unidirectional. However, some jobs can bypass some machines. In a *pure flowshop*, all the jobs are processed in the same order on *all* the machines.

In a *jobshop*, the flow of orders is not sequential. The term *open shop* designates a jobshop in which the jobs can be processed on the different machines in any order. In a *closed job shop*, only a fixed number of flow patterns exist.

In a *static* shop, all the jobs to be processed on the machines are available at time zero and all processing times are known with certainty. In a *dynamic* shop, the jobs arrive randomly and continuously over time.

2.1.2. Job Characteristics

Task or operation. It is the work done at one machine for one job.

Routing. The order in which the job is processed on the different machines.

Bottleneck job. A job that has at least one operation to be performed on a bottleneck resource.

Non-bottleneck job. A job that does not have any task that requires a bottleneck resource.

Completion time. The time when the job is ready for shipping.

Release date. The time when the production order is released to the shop floor and the job can be processed.

Flowtime. The time elapsed between the production order release date and the completion time.

Flowtime per operation. The flowtime divided by the number of tasks for a particular job.

Due Date. The point in time when the job is specified to be completed.

Planned Leadtime. The time elapsed between the customer order arrival and the job due date.

Actual Leadtime. The time elapsed between the customer order arrival and the job completion. It is the leadtime considered in this thesis, unless otherwise mentioned. It is longer than the flowtime when the job is not released immediately to the shop floor.

2.1.3. Performance measures

Lateness. The difference between the completion time of the job and the due date.

Tardiness. The difference between the completion time of the job and the due date if it is positive. Otherwise it is null.

Percentage of tardy jobs. The proportion of jobs which are completed after their due date.

2.2. *Order Review/Release*

If there is no control of the workload on the shop floor, it might be almost empty at some times and then overloaded at other times. When the shop is overloaded, expediting is necessary and confusion is created. Also too much WIP on the shop floor represents excessive money tied up in inventory. In order to prevent these outcomes, it is advisable to control the release of production orders and the flow of work after release. Control on the shop floor is often obtained using dispatch rules. These are discussed in the last section of this chapter.

Order Review/Release (ORR) aims at managing the transition of the orders from the planning system to the shop floor (Melnik, Ragatz, 1984). At a minimum, an ORR system includes the development and maintenance of an order release pool or input buffer. Once the planning system determines that an order should be released, it comes under management of the shop floor control (SFC) system. If the shop floor is overloaded the ORR planning function can decide to hold any new accepted orders in an order release pool. Otherwise, new production orders are allowed to enter the shop floor immediately.

Different mechanisms may be used in regulating production order releases. The release decisions can be evaluated either on a periodical or continuous basis. The decision to release can be made on the basis of the shop status or the pool status. Several local or global selection rules might be created to decide which jobs are released next. This process levels the workload over time so that only the jobs that are needed are in the shop

at the right moment. Bergamaschi, Cigolini, Perona and Portioli (1997) present a review and a classification of ORR in a job shop environment.

Baker (1984) presents the effects of input control on a shop with a single machine and a Poisson arrival stream. This example clearly illustrates the influence of introducing input control. He compares the performance of a shop without ORR to another one with a very simple release mechanism. Whenever the workload falls below a critical level, new jobs are released until a minimum level is attained again. The only measure considered in this study is mean tardiness. Different dispatch and due-date setting rules are used. The author concludes that the use of input control restricts the number of jobs on the shop floor and therefore reduces the scheduling possibilities. Mean leadtime naturally increases. However, Melnyk and Ragatz (1989) emphasize that the increase in the mean leadtime is a consequence of holding jobs in the release pool. As a matter of fact, a job spends less time on the shop floor itself. On the one hand, the shifting of the jobs from the shop floor to the job pool may allow reduction in the variation of the leadtimes. This allows for better delivery performance. On the other hand, by reducing the time a job spends on the shop floor, less WIP is necessary to produce the same items. Also late changes and cancellations of an order are now possible.

Wight is a pioneer in the field of input control. In his 1970 article he evaluates the consequences of uncontrolled shop loading. This situation is tackled as a leadtime problem. He points out that “the backlog is a fundamental cause of long leadtime, and leadtime can only be controlled if backlog is controlled”. Any inflation in the leadtime increases the backlog of orders since the clients need to order further in advance. If all the

orders are released to the shop, the queues increase. As a consequence the actual leadtime increases further and a vicious cycle begins. This creates confusion in the shop and the need for expediting or subcontracting. Short leadtimes enable a plant to plan its production more precisely, given that forecasts over a short period of time are more accurate. However, since even very good forecasts result in actual leadtimes that are only approximate to planned leadtimes, smoothing the pattern of input releases may still benefit performance. Wight reduces the problem of controlling order backlogs and job leadtimes to one simple rule: "THE INPUT TO THE SHOP MUST BE EQUAL TO OR LESS THAN THE OUTPUT". This rule is referred to as Input / Output (I/O) control.

Shimoyashiro, Isoda and Awane (1984) illustrate by means of a simulation, the relationship between the WIP, the leadtime and the throughput. They emphasize the fact that after a certain level of WIP has been reached, the throughput rate no longer increases significantly. In fact, only the flowtime continues to increase. There is therefore a critical level of WIP to maintain in the shop. Bechte (1988) uses interesting diagrams to show the dynamic relationships between input, output, inventory and flowtime.

In many studies on ORR, it is assumed that there is no possibility of adjusting capacity in the shop, and that all the orders are accepted. In this case, ORR is limited to input control, since the maximum output rate depends on the actual capacities and cannot be varied. Moreover, there are no interactions between the planning department and the shop floor control department and therefore there is no visibility from period to period. In this case, the load of orders cannot be adjusted by moving forward or backward some orders from one period to the next. In this context, the studies focus mostly on the effects

of introducing ORR in a shop with random arrivals and where input control and shop floor sequencing are the only control factors.

Bertrand (1983) investigates the usefulness of using workload information to predict the leadtime in a jobshop with five machines and Poisson arrivals. Two jobshops, one with and one without ORR, are included in his analysis. The ORR system keeps the total workload at a fixed level. Two different dispatch rules, Operation Due Date (ODD) and a mix of the latter and SPTT are tested. The author studies only the changes that occur for the mean lateness measure. He concludes that ORR in itself does not have any influence on the variation of lateness but rather amplifies the effect of the dispatch rule and due-date setting rule. In contrast, Bechte (1988) emphasizes that “if the planning of order entry and order release was performed carefully [...] the orders will flow through the shop without considerable delays by themselves. With low inventories the competition among the queuing orders will become easier and complex dispatching decisions more and more unnecessary. In this case operation sequencing should apply the FIFO-rule which shows the best results regarding leadtime accuracy.” This conclusion is consistent with the results of Nicholson and Pullen (1971). They argue that FCFS might be appropriate if an effective input/output control system is used.

Ragatz and Mabert (1988) compares five release mechanisms combined with four different dispatch rules in a jobshop study. One of the five release strategies is “naïve” in that it releases jobs to the shop immediately without taking any shop or job information into consideration. Two other methods use a forward planning system that releases jobs to the shop a fixed number of hours per operation ahead of their due date. One of them

(called Modified Infinite Loading or MIL) integrates the current shop load into the flow allowance calculations. The fourth method is based on the aggregate workload. The jobs with higher priority are released at the start of every day, until a specified number of jobs are reached or all the jobs have been released. The last strategy plans the release of the jobs further in advance but integrates the capacity of the shop so that the jobs scheduled do not overload the shop. The four dispatch rules used were FCFS, SPT, EDD and CR (Critical Ratio). The jobshop features five machines, a Poisson process arrival and negative exponential processing times truncated to a maximum. The number of tasks varies from one to eight. The approximate aggregate utilization level is 87%. New orders are stored in a pre-shop file during the week before they are assigned a due date and are released to the release pool. The due dates are based on the number of operations. Planned leadtimes vary from one to three weeks. The different strategies are compared through a cost structure, which includes a late delivery cost and a holding cost for both WIP and finished goods inventory. The authors conclude that the use of a release strategy is beneficial in terms of leadtime, the level of congestion in the shop, and the total costs incurred. The MIL strategy turns out to be the best performer relative to total costs. For their shop and cost structure, the CR dispatch rule performs best.

Irastorza and Deane (1974) built a Mixed Integer Linear Program (MILP) to control the workload in the shop. This program is interesting in that it does not only control the aggregate workload, but intends to balance the workload between the work centers. The program tries to match a desired workload for every work center. The variables of the program represent the orders available for release. The authors apply the

MILP to a jobshop with ten machines and exponential interarrival times. Two dispatch rules are compared: the Dynamic Slack per Operation (DSOP) and the Shortest Processing Time (SPT). SPT results in better shop and machine balance, but in higher variation in the leadtimes. The aggregate workload and the queues vary less when the shop is loaded according to the MILP solution than when the input is uncontrolled. However, the machine load balance does not improve significantly. Unfortunately, long computation times are required to solve the MILP.

A paper by Ahmed and Fisher (1992) addresses the three-way interactions between due date assignment, order release and sequencing procedures in a simulation model of a dynamic jobshop. They emphasize the importance of considering the interaction between the three factors when choosing any of the parameters for the model.

In another paper, Philipoom and Fry (1992) include an order review mechanism and relax the commonly made assumption that all the incoming orders have to be accepted. Their ORR system simply refuses new orders, either when the shop is highly congested, or when the work centers on which the new order has to be processed are busy enough. They conclude that it might be beneficial for the shop to refuse some orders instead of accepting orders that are likely to be tardy. The customer whose order is refused can look for another supplier with a better ability to deliver the order on time.

Some authors extend the ORR features, and include the possibility of small adjustments in capacity (or short-term adjustments) on the shop floor. Such a feature allows for output control, since the maximum output rate can be modified by changes in the shop capacity. Shimoyashiro, Isoda and Awane (1984) study the effects of adding

capacity to the busiest work centers. They focus on load balancing as well. The authors deal with the jobshop problem. The shop they study is fairly big (33 work centers). Each job has six tasks and the processing times are quite variable. The data was collected from a real jobshop and therefore the arrival stream is simulated with the true release dates of the jobs in the shop. The authors simulate several scenarios in which they modify the job sequence at each machine, the amount of work input, the order release sequence, and the workload balance in the shop. They then analyze the effects of limiting work input and load balancing. The load balancing is the result of a man-machine interaction. They discuss several interesting points:

- ❖ Increasing WIP does not always increase machine utilization. In fact, after a certain level of WIP has been reached, machine utilization does not increase, but flowtimes do.
- ❖ Increasing the capacity of a few overloaded work centers helps to increase machine utilization overall and reduces flowtimes.
- ❖ Load balancing is the best way to increase machine utilization and reduce the WIP.
- ❖ The dispatch rules do not play a major role if load balancing is performed and the right amount of WIP is used. Note that this result was obtained for two dispatch rules only, namely FCFS and SPO (Slack Per Operation). Therefore it is open to discussion for the general case.

Bechte (1988) describes the implementation of Input/Output control in a plastic leaves factory. The ORR maintains the load at each work center below a critical level.

The release date for the orders is a function of their due dates. At the beginning of each period, the more urgent orders are released until the maximum load limit is reached. Capacity can be adjusted when urgent orders to be released overload the shop. WIP as well as leadtimes were reduced with the new shop floor control system.

Onur and Fabrycky (1987) implemented an Input/Output control coupled with capacity adjustment (called DI/OCS). Their system consists of two stages. In the first stage an iterative search method based on a mixed linear integer program is used to generate several solution sets. These solution sets propose different capacity adjustments, depending on the jobs already in the shop, the new jobs to be released and the capacity levels of the machines. Note that the mixed linear program used in the iterative search is fairly complex. In the second stage, the most economic solution (estimated through a particular cost structure) among the ones generated in the first stage is implemented and the capacity is adjusted accordingly. The changes in the capacity are restricted to realistic norms. This control system is compared to an alternate control method where only the input can be varied (i.e. the capacity for the machines is fixed). Six machines compose the jobshop and the arrival stream to the shop is Poisson. Significant improvements are achieved with DI/OCS when the shop is heavily loaded, since the mean flowtime, the flowtime variance, the tardiness variance and the WIP level are reduced. No improvements are achieved when the shop is lightly loaded.

Melnyk and Ragatz (1988) suggest that the ORR should be part of a closed loop planning system. The planning system should attempt to release the same amount of WIP from period to period. Variations in the job pool should be taken as a signal for

adjustment of capacity. In the last few years researchers have tried to link the ORR functions with a planning system. Three studies integrate some load smoothing through the implementation of a planning procedure. The objective is to demonstrate that the effectiveness of ORR can be improved by incorporating a planning system. The planning system considered reviews the schedule at each period. When the planned load is too high, some orders are kept in the planning department. Alternatively, when the work is too low, some work is pulled forward from the next planning period. These changes are then reflected on the load in the next period. Under some specific conditions Melnyk, Ragatz and Fredendall (1991) find that this extensive smoothing improves the results dramatically. In this case, the ORR procedure helps to reduce both the leadtimes and the work-in-process inventory. Salegna (1996) emphasizes that smoothing can be a good way to increase the flexibility of the schedule, unless holding costs are prohibitive. Finally, Melnyk, Denzler and Fredendall (1992) insist on the benefits of reducing the variability of the system at all possible levels. They compare the different stages of variance reduction by first introducing some load smoothing, then an ORR system and finally reduction in the variance of the processing time. The ORR system is unable to reduce the leadtime when used together with load smoothing. In this case, immediate release is still the way to obtain the shortest mean leadtime.

Spearman, Woodruff and Hopp (1990) consider ORR within another framework: the planning system is responsible for maintaining a certain level in the pool. In other words, they consider the demand as infinite. In this case, the shop floor control department must determine the throughput level they want to achieve. Note that the

capacity of the machines is fixed. In this context, they develop a production system called CONWIP (CONstant WIP). With this system, a new order is released in the shop only when another one is completed. The authors claim that CONWIP has the benefits of a pull system and can be used in many manufacturing environments. As a matter of fact, Spearman and Zazanis (1992) state that the pull systems (like Kanban) are effective because they limit the WIP on the shop floor and not because work is pulled between stations. Spearman, Woodruff and Hopp (1990) consider CONWIP as “input-output control carried to its logical extreme” and as a “practical method of implementing input/output control at the shop floor level”. This result is consistent with Wight’s ideas. However, the assumption of infinite demand is quite restrictive.

All the input control systems considered so far try to control the total workload, and most of the shops studied were balanced. This assumption is almost never met in practice, as explained by Glassey and Resende (1988). More recently, a few authors have studied unbalanced shops and have created ORR systems that do not limit the aggregate workload, but that rather control workloads affecting only the busiest machines or bottlenecks. In this context, the releases occur at the bottleneck rate. Glassey and Resende compare four different release methods in jobshops where the jobs return several times to the bottleneck during their sojourn in the shop. The first method releases orders at a constant rate equal to the desired output rate. The second one is called the Fixed-WIP rule and releases a job every time another one is finished. The third rule keeps track of the Work En Route to the bottleneck. The last one records the Work En Route to the bottleneck in a timely manner through the use of a “virtual inventory”. In this case, the

Work En Route to the bottleneck is weighted with a time factor. For example, a bottleneck job that still has ten operations to be performed before it reaches the bottleneck has a lesser weight than the one for which operation on the bottleneck is next. The last strategy outperforms all the other ones in terms of throughput and leadtime in their experiments. The second and third strategies are relatively close to the first one. The first strategy (uniform release) results in higher leadtimes for a comparable level of throughput.

Roderick, Phillips and Hogg (1992) compare the CONWIP strategy with a bottleneck strategy for a simulated production facility with a mix of three different products. The arrival process is Poisson, and jobs are added to a pool each day. They assume that the Master Production Schedule (MPS) always has orders available to be processed. All the products are processed by the bottleneck(s). Four different shops are tested, all with a flowshop routing structure. The throughput, the WIP and percentage tardy are the three measures used. They conclude that CONWIP is slightly superior, although some of their results are inconclusive since in a few situations one strategy is superior on one measure while being inferior on another.

ORR systems based on bottlenecks are relatively new. However such systems might be promising. As a matter of fact, Goldratt developed a production control system and a scheduling theory based on the constraints of the production facility. This system aroused an important change in the production world. Since the ideas developed by Goldratt apply to input control, his theory is summarized in the next section.

2.3. From the Optimized Production Technology (OPT) to the Theory Of Constraints (TOC)

Eli Goldratt is a former Israeli physicist who came into business by helping a friend to improve the production schedule of his chicken-coop factory. Goldratt adapted one of the algorithms he had developed in physics for optimizing a large number of system variables. His algorithm happened to improve the factory so much that the production rate tripled with the addition of only one worker (Mewborne, 1989).

2.3.1. Optimized Production Technology (OPT)

Goldratt's first business experience results in the creation of the Optimized Production Technology (OPT) software. Goldratt claims that the scheduling problem is not overwhelming if the problem is tackled from the right angle. Goldratt admits that it is very difficult to have a balanced shop. Therefore he considers the scheduling process in the context of an unbalanced shop, and explains how to take advantage of the bottlenecks to create a schedule. The scarcest resources (bottlenecks) limit the throughput. Therefore the scheduling process should be developed around them. Once bottlenecks are scheduled, the workflow should be determined so that jobs arrive at the bottlenecks to meet the bottleneck schedule. Non-bottleneck machines are used to produce only what is required to feed the schedule for the constraining resource. Surplus production capacity not required to feed bottlenecks in a timely manner should not be used, since it only

results in excessive WIP inventory. Goldratt differentiates the words *activation* and *utilization* of a machine. He considers that the machine is *utilized* only if its *activation* will increase the throughput.

It results from the above statement that the non-constrained resources have some idle time. It is important not to view this as inefficiency but rather as an opportunity to improve the production process. Since there is idle time, the transfer batch size can be reduced in two ways. Either the workers at the non-bottleneck machines can pull material from feeding stations more frequently, or the number of setups can be increased. Although the process batch might be more than one, the transfer batch can be reduced through surplus time available. This lot splitting allows for the material to go through the shop more quickly.

Finally, Goldratt insists that the only way to improve the throughput is to free some time at the bottleneck, for example by reducing the processing times at the bottleneck machine or by adding capacity. Any time saved at another machine will not facilitate a higher throughput.

All the ideas mentioned above are contained in nine rules (Lundrigan, 1986):

1. Balance the flow, not capacity.
2. Constraints Determine Non Bottleneck Utilization.
3. Activation Is Not Always Equal to Utilization.
4. An Hour Lost at a Bottleneck Is an Hour Lost for the Entire System.
5. An Hour Saved at a Non Bottleneck is a Mirage.
6. Bottlenecks Govern Throughput and Inventory.

7. Transfer Batch Should Not Always Equal a Process Batch.
8. Process Batches Should Be Variable, Not Fixed.
9. Set the Schedule by Examining All the Constraints Simultaneously.

The main advantages of using OPT are reduced WIP and increased throughput. As a result the operating costs will decrease and the cycle times will improve. The time for the software to generate a schedule appears to be reasonably short (Meleton, 1986). However, the quantity of data to update is enormous and costly. Its accuracy is critical too. This appears to be one of the main drawbacks of the software. As well, the secrecy of the algorithm and the fact that its results are counterintuitive to traditional practice makes it difficult to accept. Who would agree to spend several hundred thousand dollars for software they do not understand? Meleton (1986) thinks of the software as a great modeling or simulation tool. He thinks that the software is mainly useful for traditional jobshops, since the repetitive environments tend to balance a line relatively quickly and therefore the bottlenecks can be eliminated early. Lundrigan (1986) summarizes the power of OPT as follows:

“OPT integrates the best of MRP and JIT, combines them, and uses the power of the computer to elevate production and inventory control to a new level”.

2.3.2. Theory Of Constraints (TOC)

The Theory Of Constraints formalizes and extends the principles originally used in developing OPT software and later communicated in “The Goal” (Goldratt and Cox,

1992) and “It’s Not Luck” (Goldratt, 1994). Mainly, Goldratt insists that a company should first recognize that *its goal* is to make money now and in the future. All the decisions must be made considering this goal. Therefore the nine rules of OPT are replaced by the following five process improvement steps (Schrage and Ronen, 1990) in TOC:

1. Identify the system constraint(s).
2. Decide how to exploit the constraint(s).
3. Subordinate everything else to the above decision.
4. Elevate the system constraint(s).
5. If, in the previous step, a constraint has been broken, go back to step 1, but do not let “inertia” become the system constraint.

The first step invites the practitioner to identify what prevents the company from selling more throughput. Note that the term “bottleneck” has been replaced by the term “constraint”, which is more general. A constraint is defined as anything that limits a system from achieving higher performance relative to *the goal*. Constraints can be the resources that have the least excess capacity on average. The constraint can also be anything internal or external to the company that prevents the company from achieving higher performance. For example, the market can be a constraint if the company is not able to sell everything it can produce.

The second step encourages the production manager to make the right decisions about the constraint. Goldratt insists that one should think in terms of the profit per item divided by its processing time on the bottleneck rather than just in terms of profit per

item. One product may appear to have a larger profit margin than another one. However if it uses substantially more time at bottleneck resources only a few of these items can be produced before capacity is exceeded. This means that a product using less time on bottleneck machines may yield higher profits even though margins are less substantial.

Step 3 states that the release of material should be dictated by the needs of the constraint under consideration. This is coordinated by the so-called drum-buffer-rope (DBR) scheduling process. The drum is a precise schedule for the constraint. The rope represents the time necessary for material to move from release to the constraint and from the constraint to shipping. Two buffers are created in DBR. One buffer contains all the material that is scheduled to be at the constraint at any time (constraint buffer) and the other buffer contains all the material that is scheduled to be ready for shipping at any moment in time. In short, the first buffer protects the constraint from starving while the second one prevents the orders from being late.

This scheduling process is improved by the use of inventory dollar days or throughput dollar days measures. They penalize the worker for working ahead of schedule (inventory dollar days) or behind schedule (throughput dollar days). If the worker works ahead of schedule he creates inventory. If he is late, the bottleneck might be starving and throughput can be lost. The longer the item is ahead of or behind schedule, the higher the penalty. Thus the worker is encouraged to follow the schedule as closely as possible.

Steps 4 and 5 focus on the notion of continuous improvement. The company should strive to relax the existing constraint, until the point when it is no longer a

constraint for the system. However, once this constraint has been removed (or elevated), another constraint will naturally appear. Therefore the cycle begins again. These last two steps are essential for continuous improvement and for the success of a company in the long run.

TOC is the formalization and the evolution of the techniques used to create the OPT software. TOC extends beyond production control. And thus, only the concepts relevant to this research are presented here.

2.3.3. Studies relevant to TOC

Several studies describe firms that have implemented TOC with success. Gardiner, Blackstone and Gardiner (1994) insist that TOC should be throughput oriented. Once the internal constraints have been elevated, and therefore do no longer exist, it is essential for the company to conquer a new market. The authors relate the changes that appeared at Kent Moore, a company building house cabinets, and at Valmont Industries.

The DBR technique has been adapted to remanufacturing in a military rework depot (Guide and Ghiselli, 1995). Standards relating to parts routings and processing times are not available in this type of plant since the amount of work and the necessary part routings depend on the particular item being remanufactured. Through the implementation of TOC, the depot achieved a 50% reduction in WIP and a 40% increase in turnaround time.

Schrageheim, Cox and Ronen (1994) explain how to modify TOC for a process

flow industry. Reimer (1991) reports the transition from an MRP system to a TOC production control system in which MRP only performs the scheduling of the non-constraint parts. Lambrecht and Decaluwe (1988) analyze the main advantages of TOC over the JIT philosophy. They note that the Kanban system used within JIT is very sensitive to variations and depends on how well a company manages capacity. They believe that the TOC approach prevents problems while the JIT approach tries to solve problems only after they have appeared. The improvement process in JIT often calls for reducing WIP and then solving whatever problems appear. On the contrary, TOC first maintains the WIP necessary to prevent problems, and then tries to improve the production process.

Fry and Smith (1987) describe how ABC Tool, a western manufacturer, decided to introduce input/output control, as described by Wight. The implementation of Input/Output control follows some of the steps of TOC. After shifting to a global measurement system to determine the bottlenecks, they decided on the size of the buffers to protect the bottlenecks. Also, production lot sizes to reduce WIP and allow for a more level final assembly schedule were determined. They then educated the workers to work only on the right items. Finally, the input was set equal to the output. The results achieved under these circumstances turn out to be impressive. The company reduced its WIP by 42% and increased the service level by at least 20%.

2.4. Job sequencing

Job sequencing is the last step in the shop floor control system. It consists of establishing in which order a set of waiting jobs are processed on a machine. In a static environment, the objective of sequencing is usually to order a given number of jobs on a machine so that the completion time of the last job processed is minimum. This is referred to as makespan minimization. In a dynamic environment, the jobs arrive stochastically and the mix of jobs varies through time. In this kind of shop, the jobs have to be sequenced with the aim of minimizing some performance measure other than makespan. The most common measures are mean tardiness, average flowtime, proportion of jobs tardy and maximum flowtime.

Sequencing is often performed using job-dispatching techniques. The next job to be processed is chosen by following some specific rules. The method used to dispatch the jobs can be more or less sophisticated. It usually consists of a simple heuristic rule that is based on information about the job itself (local rule) or on the shop status (global rule). The simplest rules are based on the order of arrival in the queue (First Come First Served or FCFS), on the processing time of the tasks, (Shortest Processing Time (SPT) or Longest Processing Time (LPT)) or on the due date (Earliest Due Date or EDD). Rules that use combinations of these and other criteria have been developed as well.

More sophisticated dispatch rules use information about the shop status in addition to job information. For example, measures such as queue lengths are often used to indicate shop status elements relevant to dispatching. Panwalkar and Islander (1977)

summarized the research on this topic and listed over one hundred rules. They concluded none of the rules provide the best solution in every case.

The choice of a dispatch rule depends mainly on the performance measure and the information available. Effectiveness is influenced by uncontrollable factors such as machine breakdowns or unpredictable arrivals but also by the shop characteristics. Some guidelines for dispatch rule selection have been established despite these complications (Melnik, 1985). It has been found that simple rules often tend to be as effective as more sophisticated rules. Due date dependent rules, such as EDD, work well when the due dates “are both attainable and relatively loose” (Melnik, 1985). Otherwise, the SPT rule often produces better results. Philipoom and Fry (1990) study the relative performance of popular dispatching rules for an unbalanced jobshop versus a balanced jobshop and conclude that most of the dispatch rules are robust regarding the balance of shop loads. In the same study they conclude that the work flow structure (in their case an open job shop versus a pure flow shop) modifies the performance of only a minority of the rules. SPT is shown to be affected neither by an unbalance in the shop load nor by a modification in the work flow structure.

Melnik, Denzler and Fredendall (1992) investigate the influence of system variance on job sequencing. They compare FCFS and SPT dispatching for processing times which follow either a negative exponential distribution or a uniform distribution with a much smaller variance. Their results indicate that the processing time coefficient of variation (CV_p) contributes to the performance of these rules. The SPT rule is shown to be a poor choice when the coefficient of variation of the processing times is small and

the objective is to minimize either the mean tardiness or the percentage of tardy jobs.

Deciding which rule is appropriate for a given situation depends on many factors and their interactions. Determining relative performances is still frequently a matter of experimentation. Dispatch rules can improve the shop performance only to limited extent. For example, factors contributing to external variability, such as the interarrival time distribution, greatly affect performance regardless of the dispatch rule under consideration. Melnyk, Denzler and Fredendall (1992) study a jobshop in which the number of tasks per job varies from two to six. They conclude that if most of the variability external to the shop floor can be removed, the effect of the dispatch rule on the performance is not nearly as important. In fact, the FCFS dispatch rule may be best, since it is simple and reduces the variance of the actual leadtimes.

2.5. Research goal

TOC and previously developed ORR systems, such as those advocated by Wight, promise to improve manufacturing performance by reducing and stabilizing WIP requirements. There is a general consensus that the workload in a production facility should be controlled but the way to achieve this control is open to debate. The Input/Output control ideas developed by Wight suggest that the total workload in the shop has to be monitored and should be kept constant. TOC is innovative in that it advocates maintaining just enough work in front of the busiest machines to make sure

that these machines do not suffer from disruptions due to uncontrollable variations in the shop. However, as mentioned earlier, queues tend to build in front of the bottleneck machines when the shop becomes overloaded in any event. Therefore the control of the total workload regulates these specific queues anyway, although somewhat indirectly. It therefore can then be questioned if there is any benefit to use input control based on the bottleneck needs rather than on aggregate workload. Little research has been devoted to Bottleneck Input Control, and many questions remain unanswered. The purpose of this thesis is to get a better understanding of the role of the bottleneck in the shop and to see how the bottleneck affects the selection and performance of various input control strategies.

Most studies have been carried out in a jobshop within which only a limited number of products were processed. Moreover, all the jobs were processed by the bottleneck. This assumption is relaxed in this thesis, as the importance of the flow pattern in a bottleneck release strategy and in an aggregate release strategy is investigated. The severity of the bottleneck is varied to find the effect the bottleneck has on the WIP level and the leadtime, using both control strategies.

3. Experimental framework

The previous chapter presented an overview of trends in production control relevant to order release. The question arose as to whether a Bottleneck Input Control strategy would be a better choice than an aggregate release strategy (i.e. a strategy based on the total or aggregate workload). In this chapter, the experimental framework to compare their relative performances is presented. This framework must be general enough, so that the results are valid under different circumstances, yet simple enough so that its complexity does not make it too hard to understand or to implement. It will be used for the experiments carried out in this study. By means of discrete-event simulation the different release strategies will be compared. Also, part of this framework is used for an analytical model developed in the next chapter.

3.1. General model description

The features of the shop are described first. The shop has six machines, numbered from one to six. This is consistent with studies in the current literature, many of which are based on four to six machines. Moreover, Conway et al. (1988) state that for a perfectly balanced flow line, with an unlimited availability of raw material, “the loss of capacity occurs in the first five machines; additional machines cause little additional loss”.

Although in the research model the input to the shop is limited, it can be conjectured that this result is still approximately valid, and that the most important loss in capacity will still appear within the first few machines.

The production environment is assumed to be dynamic since dynamic shops are more appropriate to study input control. Demand is assumed to be variable with the order arrivals defined by a Poisson process. The interarrival time distribution is negative exponential with a mean of μ_A . The time unit has been arbitrarily chosen as an hour.

The routing of each job is independent, with probabilities for visiting various machines specified by a transfer matrix (Hax and Candea, 1984). This matrix enables any type of shop, ranging from a flowshop to a jobshop, to be modeled. The number of tasks in each job follows a discrete uniform distribution. Both the number of tasks and the routing are established as the job is created.

The mean processing times, μ_P , and the coefficients of variation, CV_P , are set as parameters for each machine. The processing time distribution consists of two parts, a constant and a variable part. For the variable part, the user has the choice between a Normal distribution and an Erlang distribution, the k-parameter of which can be set by the user. For the Normal distribution the constant part is set to μ_P . The variable part is then a representation of a Normal distribution with mean 0 and standard deviation σ . The latter is calculated as $\sigma = \mu_P * CV_P$. If the processing time goes negative it is set to zero automatically. If the Erlang distribution is selected, then the following equations are solved:

$$\mu_p = \mu_c + k * \mu_E \quad \text{Equation 3-1}$$

$$CV_p = \frac{\sqrt{k} * \mu_E}{\mu_c + k * \mu_E} \quad \text{Equation 3-2}$$

where μ_c is the constant part and $k * \mu_E$ the mean of the Erlang distribution. The solution to these equations leads to the following results:

$$\mu_c = \mu_p * (\sqrt{k} - CV_p) / \sqrt{k} \quad \text{Equation 3-3}$$

$$\mu_E = \mu_p * CV_p / \sqrt{k} \quad \text{Equation 3-4}$$

The Normal and the Erlang distributions seem to be appropriate to represent processing times. Real processing times in industry have been found to follow various distributions. However, it has been observed that the coefficient of variation has more influence on the results than the shape of the distribution itself. This explains why many different distributions are used in the literature to model processing times.

There is no restriction on the length of the queues at each machine. Different dispatch rules can be used to manage priorities within these queues. The ones selected are listed in Table 1.

The due dates used in the due-date dependent dispatch rules are set using one of the following methods:

1. Total Work Content (TWK) rule. The leadtime allowance is proportional to the processing time. In this case,

$$DueDate_of_job_i = Time_of_job_creation + k_{TWK} * \sum_{j=1}^n p_{ij}.$$

2. Number of Operation (NOP) rule. The leadtime allowance is proportional to the number of operations, and

$$DueDate_of_job_i = Time_of_job_creation + k_{NOP} * n_i.$$

3. Processing Plus Waiting Time (PPW) rule. Under the assumption that the waiting time is identical at all the machines, the leadtime allowance is proportional to the total processing time and the waiting time in the queues. In this case, the due date is computed as follows:

$$DueDate_of_job_i = Time_of_job_creation + \sum_{j=1}^n p_{ij} + k_{PPW} * n_i.$$

In the above formulas, n_i is the number of operations in job i , p_{ij} is the processing time of job i on machine j , and k_{NOP} , k_{TWK} and k_{PPW} are constant multipliers whose values are usually determined experimentally.

Note that the operation due date is computed as if the job consisted of only the current operation, and the value $Time_of_job_creation$ is set equal to the time of arrival in queue.

The following list includes some of the additional general assumptions underlying the model:

1. All production from the shop can be sold. The market is not a constraint.
2. All the jobs are considered to contribute equally to profits. It is not economically beneficial to produce one type of job instead of another.
3. All raw materials are available when needed.

4. All setup times are negligible. Alternatively it can be considered that setup times are included in processing times since every job is different.
5. There is no down time for the machines and the latter produce parts that are free of defects.
6. The transfer resources (if any) are always available and the transfer times are negligible.
7. Every resource can process only one job at a time and no preemption is allowed.

Dispatch rule	Abbreviation	Priority
First-Come First Served	FCFS	The first job arrived in the queue is served first
Shortest processing time truncated	SPTT	The job with the shortest processing time has the highest priority, unless some jobs have been waiting for more than 15 hours. In this case, these jobs are sorted on a first come, first served basis and receive top priority
Earliest Due Date	EDD	The job which is due first will be processed first
Operation Due Date	ODD	The job which is due first for the current operation will be processed first
Smallest Critical Ratio	SCR	The job with the smallest ratio (<i>Due Date-Current time</i>)/ <i>Rem. Proc. time</i> has the highest priority
Operation Critical Ratio	OCR	The job with the smallest ratio (<i>Operation Due Date-Current time</i>)/ <i>Proc. time of the current task</i> has the highest priority

Table 1: List of dispatch rules

3.2. *Bottleneck machine*

The bottleneck machine is defined as the resource that has the least excess capacity. It has the greatest effect on performance. Hereafter, the terms constraint and bottleneck are used interchangeably.

A machine can become a bottleneck if its mean processing time is longer than that of the other machines and, on average, the machine processes at least as many jobs as the other machines. Alternatively, a machine can become a bottleneck if more jobs are processed on this machine than on the others and the mean processing time is at least as large. Such a bottleneck could be created in the research model by modifying the probability routing matrix so that there is a higher probability for job transfers to the bottleneck machine.

It was decided that the bottleneck would be created using longer mean processing times rather than receiving more jobs than the other machines in the actual experimental runs. The main reason is that there is no straightforward way of modeling a flowshop if the frequency of visits is used to create bottlenecks.

3.3. *Release strategies*

The Input/Output control proposed by Wight (see section 2.2) and the input control based on TOC (see section 2.3.2) are now developed for the research needs of this

study. Although they can be implemented with many distinctive details, only a small number of features were included in this study since the objective is to understand the importance of the bottleneck in the release process.

3.3.1. The Maximum Hours Strategy (MH)

In accordance with Wight's observations, the input to the shop cannot exceed the output of the shop. In order to prevent the workload from becoming excessive, the amount of work in the shop must be limited in some way. Given that all the jobs have a different number of operations, it was decided that work content (or WIP) rather than the number of jobs in the shop should be used as a workload measure. The jobs are described in terms of time necessary to complete them. Arbitrarily, the time unit chosen is the hour. Work content is defined as the number of remaining working hours that are necessary to complete all the jobs that have already been released to the shop. When the workload exceeds a certain trigger level (called Maximum Hours) new customer orders are held in an order release pool until the work content decreases below the Maximum Hours level. When the workload drops below the trigger level, new jobs are released into the shop and their total processing times are added to the work content as long the workload (before the release) is below the Maximum Hours level or there are no jobs in the release pool. As previously mentioned, all the jobs are equally important and therefore they are released to the shop in the order of arrival into the release pool. The jobs are 'pushed' between the machines required for further operations.

3.3.2. Bottleneck Input Control (BIC) strategy

In the Bottleneck Input Control strategy it is desirable to feed work to the bottleneck machine so that it is never starving, unless there is no more work to release, and yet keep the queue ahead of it to the minimum required length. In order to achieve this goal, it is beneficial to know how much work is En Route to the bottleneck at any moment in time. Every time a new job is released into the shop its processing time on the bottleneck machine is added to a variable which represents the constraint buffer in DBR scheduling. When this variable is above a critical value there is enough Work En Route to the bottleneck and releasing more jobs to the shop would only increase the WIP in the shop needlessly. Hence the jobs are held in a release pool until the variable falls below the critical level. When a job is started on a bottleneck the variable is reduced by subtracting the bottleneck processing time of this job. Once the critical level is reached the release of new jobs is triggered. Release continues until the critical level has been reached again.

Since not all the jobs have the same routings, not all the jobs are processed on the bottleneck machine. The non-bottleneck jobs are released in the shop as soon as they are created since they require only machines with excess capacity. The work is again pushed between stations. The throughput and inventory dollar days measure advocated by TOC are not used in this release strategy.

3.4. *The bottleneck priority rule (BNPR)*

An optional rule has been added to the model so that, when it is active, jobs that have yet to be routed to the bottleneck machine have priority on any machine over those jobs that do not need to visit a bottleneck machine. This is referred to as the bottleneck priority rule (BNPR). Whenever there is a job in queue that must subsequently go through a bottleneck, it is processed first. It will then be available to feed the bottleneck resource more quickly. This optional priority selection rule is used for both strategies, although it is best adapted to the Bottleneck Input Control strategy.

3.5. *Comparison of the strategies*

The implementation of the ORR strategies changes the performance of the shop. As was mentioned in the preceding chapter, the ORR usually increases the actual leadtime but reduces the level of work-in-process inventory. The use of the release strategy is a trade-off between a short leadtime and a low WIP. The performance of each strategy is going to be compared on the basis of this trade-off. Since the level of throughput is a key element in the performance, this measure is taken into account in the analysis as well.

4. Queuing model

An analytical model is often used to obtain a better understanding of a complex system, such as a production system. In a queuing model, all the individual jobs that compose the production system are aggregated so that the characteristics of an “average” job can be described. The purpose of this chapter is to develop a queuing model to gain some insight into the relative performance of the release strategies as described in the previous chapter.

The next section is devoted to the presentation of common assumptions underlying the queuing model. The formulas for the queuing model are developed in section 4.2. In section 4.3, an explanation of how the two release strategies are adapted to the queuing model is given. In section 4.4, the values of the parameters are presented. Finally, in the last two sections, the results are provided and analyzed.

4.1. *General assumptions*

Queuing analysis of a production system consists of decomposing the system into a network of single station queues. The nodes of the network represent the resources whereas the arcs represent the flows of orders. External nodes are added to describe the outside world, from where jobs arrive and to where they go to once they leave the system.

The flow of orders is random and a transfer matrix is used to describe the transitions between the nodes. The arrival stream and the processing time distributions of the machines are described in terms of their mean and standard deviation of variation. The ratio of the mean to standard deviation, known as coefficient of variation, can therefore be used to describe relative variability. The jobs are processed on a first come first served basis and the queues have an infinite capacity. Moreover there is no limit on the number of jobs in the shop.

4.2. *Formulas development*

The system developed here is based on the queuing relationships described by Whitt (1983). A summary of the formulas to be used later is presented below. The reader can refer to Whitt (1983) for further explanations.

The model is a decomposition of a shop with n machines into a network of $GI/G/1$ queues. The flowtime of a job is made of two components: the sum of the waiting times in each queue and the sum of processing times on each machine. Although the mean processing time is given in this problem, the expected waiting time must be computed for every queue. The Kraemer and Langenbach-Belz equation is a good approximation of the waiting time at a given machine:

$$EW_i = \frac{1}{\mu_i} * \frac{(C_{at}^2 + C_{pt}^2)}{2} * \frac{\rho_i}{1 - \rho_i}$$

Equation 4-1

where : EW_i - expected waiting time at machine i ,

μ_i - mean service rate at machine i ,

ρ_i - utilization level of machine i and is equal to λ/μ_i ,

C_{pi} - processing time coefficient of variation at machine i ,

C_{ai} - interarrival time coefficient of variation at machine i .

In order to calculate the waiting time at any machine, the coefficient of variation of the arrival stream has to be estimated. If the network is a flow line, it is easy to compute the expected waiting time at the first machine, since the mean and coefficient of variation of both the interarrival stream and processing times are known. However, the waiting time at any other machine i ($i=2, \dots, n$) depends on the coefficient of variation of its interarrival time. This is equal to the coefficient of variation of the interdeparture time at machine $i-1$. For a GI/G/1 queue, this coefficient is described by Marshall's formula (Whitt, 1983):

$$C_{di}^2 = C_{ai}^2 + 2\rho_i^2 C_{pi}^2 - 2\rho_i(1-\rho_i)\mu_i EW_i \quad \text{Equation 4-2}$$

where C_{di} - interdeparture time coefficient of variation at machine i .

By substituting Equation 4-1 into this formula, C_{di} can be approximated as follows.

$$C_{di}^2 = \rho_i^2 C_{pi}^2 + (1-\rho_i^2)C_{ai}^2 \quad \text{Equation 4-3}$$

When the network is not a flow line, the incoming stream at a machine originates from several sources. In the same fashion the outgoing flow is split into several streams.

Therefore a transition matrix q_{ij} is necessary to describe the flow pattern. Jobs leaving a machine i are selected independently to go to machine j with probability q_{ij} . The interdeparture time coefficient of variation C_{ij} for jobs transiting from machine i to machine j depends on q_{ij} and C_{di} , as shown in the following equation:

$$C_{ij}^2 = q_{ij} C_{di}^2 + 1 - q_{ij} \quad \text{Equation 4-4}$$

By substituting Equation 4-3 into the above equality, it follows that:

$$C_{ij}^2 = q_{ij} (\rho_i^2 C_{pi}^2 + (1 - \rho_i^2) C_{ai}^2) + 1 - q_{ij} \quad \text{Equation 4-5}$$

The next step is to estimate the interarrival time distribution when several input streams are taken into account. The following system of linear equations needs to be solved to determine the arrival rate λ_j at each of the machines.

$$\lambda_j = \lambda_0 q_{0j} + \sum_{i=1}^n \lambda_i q_{ij} \quad j = 1, \dots, n \quad \text{Equation 4-6}$$

where λ_0 - arrival rate of new jobs to the shop,

λ_j - arrival rate of jobs to machine j ,

q_{0j} - proportion of new jobs whose first operation is on machine j ,

n - number of machines in the shop.

Once the values λ_j are established, the coefficients of variation C_{aj} can be estimated through the use of the asymptotic method:

$$C_{aj}^2 = p_{0j} C_{0j}^2 + \sum_{i=1}^n p_{ij} C_{ij}^2 \quad j = 1, \dots, n \quad \text{Equation 4-7}$$

where $p_{ij} = \lambda_i q_{ij} / \lambda_j$ represents the proportion of jobs going into machine j that arrive from

machine i , and C_{aj} represents the coefficient of variation for jobs arriving from the outside world to machine j . The first part of Equation 4-7 represents the squared coefficient of variation of the interarrival times for new jobs. The second term is the superposition of the squared coefficients of variation of the interarrival times for job streams originating from other machines.

After substituting for C_{ij} using Equation 4-5, Equation 4-7 becomes:

$$C_{aj}^2 = p_{0j} C_{0j}^2 + \sum_{i=1}^n p_{ij} \left[q_{ij} (\rho_i^2 C_{pi}^2 + (1 - \rho_i^2) C_{ai}^2) + 1 - q_{ij} \right] \quad \text{Equation 4-8}$$

where machine utilization ρ_i is equal to λ_i/μ_i . Again, the search for the C_{aj} 's values are determined by solving a system of linear equations.

Finally, the expected total flowtime per job is equal to the sum of the processing and waiting times:

$$EF = \sum_{i=1}^n \left(\left[EW_i + \frac{1}{\mu_i} \right] \frac{\lambda_i}{\lambda_0} \right). \quad \text{Equation 4-9}$$

4.3. Incorporation of the two release strategies

The two strategies presented in section 3.3 are designed to regulate the workload in the shop. To achieve this goal, the Maximum Hours (MH) strategy postpones the release of new jobs if the shop is too busy. The Bottleneck Input Control (BIC) strategy allows new bottleneck jobs to enter only if the Work En Route to the bottleneck is below

a critical level. Unfortunately, it is difficult to incorporate the two release strategies in a queuing model.

In order to emulate somewhat the mechanisms of the strategies, a dummy machine with a constant processing time is added to the shop. If the MH strategy is being implemented, all the incoming jobs are first processed on the dummy machine. This dummy machine is assumed to have a processing time coefficient of variation equal to 0. If the BIC strategy is chosen, only the bottleneck jobs are first routed to the dummy machine. The coefficient of variation of the interarrival times for the jobs released to the shop is equal to the interdeparture time coefficient of variation of the dummy machine. From Equation 4-3, it follows that this coefficient of variation is low if the machine utilization is high. Therefore, the longer the processing time of the dummy machine, the more the variation due to the interarrival times will be leveled out.

Note that the time a job spends in queue at the dummy machine is comparable to the time a job spends in the job pool, when an ORR strategy is used. The processing time of the dummy machine can be subtracted out in analyzing the job flowtimes and WIP inventory. The processing time of this machine just shifts the arrival stream by a constant. However, there is an important difference between the release strategies as described in 3.3 and the “imitation” used in this queuing model. The queuing model tries to reduce the variance in the shop by delaying arrivals that are too close together and by bringing closer together arrivals that are far apart. It does neither control the aggregate workload, nor the Work En Route to the bottleneck. In other words, the timing of arrivals to the

shop is being controlled rather than the shop load, as measured by processing time requirements. This is the only approach that appears possible with an analytical model.

4.4. Model parameters

The six machines of the production system modeled are numbered from 1 to 6. The dummy machine is machine 7. The arrivals to the shop follow a Poisson process with a mean interarrival time of 0.9. Each job is composed of five tasks. Machine number 4 is assumed to have a longer average processing time than the other machines and therefore has been chosen to be a bottleneck. The average processing time per machine is equal to 0.95. This results in an average shop utilization of 88 percent ($0.95 \times 5/6 \times 1/0.9$). The coefficient of variation is set to 0.5 at each machine. Three different levels have been chosen for the bottleneck machine:

Level 1. There is no bottleneck.

Level 2. The average processing time is 0.94 on machines 1, 2, 3, 5 and 6, and 1 on machine 4. The shop has a *light* bottleneck.

Level 3. The average processing time is 0.935 on machines 1, 2, 3, 5 and 6, and 1.025 on machine 4. The shop has a *severe* bottleneck.

Both flowshop and jobshop models will be studied. In the flowshop model, five operations per job means that each job bypasses one machine randomly. Therefore, six possible routings exist, as shown in Table 2. In the jobshop model, a job can enter the system on any machine, and can go from one machine to a different one with equal

probability. A job can be processed twice on the same machine, but not consecutively. Hence it can be computed that there are more than 3000 possible routings for the jobshop model.

Routings
1 2 3 4 5
1 2 3 4 6
1 2 3 5 6
1 2 4 5 6
1 3 4 5 6
2 3 4 5 6

Table 2: List of the possible routings for the flowshop

4.5. A spreadsheet implementation

In section 4.2, the formulas for estimating the average time a job spends in the production system were presented. However, the use of these formulas requires solving two systems of linear equations. In the next section it is shown how these two systems can be solved using a spreadsheet framework. The construction of the matrix q_{ij} will be explained in section 4.5.2.

4.5.1. The EXCEL spreadsheet

	A	B	C	D	E	F	G	H	J	KL	M	N	O	P	Q	R	S
16	Arrival										M1	M2	M3	M4	M5	M6	M7
17	Rate	1.11 (arrival rate)									Rate	1.05	1.05	1.05	1.05	1.05	1.18
18	Mean	0.90 (mean interarrival time)									Mean	0.95	0.95	0.95	0.95	0.95	0.85
19	Variance	0.81									Variance	0.23	0.23	0.23	0.23	0.23	0.00
20	CVa0	1.00									CVs	0.50	0.50	0.50	0.50	0.50	0.00
21																	
22	Q-matrix (prop. of 'i' that goes into 'j')										P-matrix (prop. into 'j' that comes from 'i')						
23																	
24	From\To	M1	M2	M3	M4	M5	M6	M7	Dep.	From\To	M1	M2	M3	M4	M5	M6	M7
25	Arrival	0.17	0.00	0.00	0.00	0.00	0.00	0.83	0.00	Arr.	0.20	0.00	0.00	0.00	0.00	0.00	1.00
26	M1	0.00	0.80	0.20	0.00	0.00	0.00	0.00	0.00	M1	0.00	0.80	0.20	0.00	0.00	0.00	0.00
27	M2	0.00	0.00	0.80	0.20	0.00	0.00	0.00	0.00	M2	0.00	0.00	0.80	0.20	0.00	0.00	0.00
28	M3	0.00	0.00	0.00	0.80	0.20	0.00	0.00	0.00	M3	0.00	0.00	0.00	0.80	0.20	0.00	0.00
29	M4	0.00	0.00	0.00	0.00	0.80	0.20	0.00	0.00	M4	0.00	0.00	0.00	0.00	0.80	0.20	0.00
30	M5	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.20	M5	0.00	0.00	0.00	0.00	0.00	0.80	0.00
31	M6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	M6	0.00	0.00	0.00	0.00	0.00	0.00	0.00
32	M7	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00	M7	0.80	0.20	0.00	0.00	0.00	0.00	0.00
33	M8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	M8	0.00	0.00	0.00	0.00	0.00	0.00	0.00
34																	
35	Determine job arrival rate:																
36																	
37		Constraints for arrival rate to machines:									Constraints for CV sq. of arrivals to machines:						
38																	
39		Lambda1		0							CVa1 sq.		0				
40		Lambda2		0							CVa2 sq.		0				
41		Lambda3		0							CVa3 sq.		0				
42		Lambda4		0							CVa4 sq.		0				
43		Lambda5		0							CVa5 sq.		0				
44		Lambda6		0							CVa6 sq.		0				
45		Lambda7		0							CVa7 sq.		0				
46		Lambda8		0							CVa8 sq.		0				
47																	
48	System Performance Measures:																
49																	
50		Lambda	Utiliza	CVa	sc	CVd	sc	E(Wi)	E(Fi)								
51																	
52	M1	0.93	0.88	0.60	0.33	2.95	3.90				2.46	3.25	2.28				
53	M2	0.93	0.88	0.55	0.32	2.78	3.73				2.31	3.11	2.14				
54	M3	0.93	0.88	0.54	0.32	2.74	3.69				2.29	3.08	2.12				
55	M4	0.93	0.88	0.53	0.31	2.72	3.67				2.27	3.06	2.10				
56	M5	0.93	0.88	0.53	0.31	2.72	3.67				2.27	3.06	2.10				
57	M6	0.93	0.88	0.53	0.31	2.72	3.67				2.27	3.06	2.10				
58	M7	0.93	0.79	1.00	0.38	1.57	2.42				1.31	1.31	1.21				
59	M8	0.00	0.00	0.00	0.00	0.00	0.00				0.00	0.00	0.00				
60																	
61											15.2	19.9	14.0				

Figure 2: Example of the Excel spreadsheet

A sample spreadsheet of the model, implemented in Excel 5.0 is presented in Figure 2. This spreadsheet models eight machines and thus is an extension of the spreadsheet developed by Enns (1997) for four machines. His model has been validated

against simulation results and has been found to give good approximations. Note that the last machine is not used and therefore all the elements relative to this machine are set to 0. Recall that machine 7 is the dummy processor. The model is composed of six “real” machines.

As shown in Equation 4-6, a system of linear equations needs to be solved to find the values of the arrival rates λ_j :

$$\lambda_j - \lambda_0 q_{0j} + \sum_{i=1}^n \lambda_i q_{ij} = 0 \quad .$$

The eight equalities are entered in cells D39:D46, as shown in Figure 2. The feasible solutions found using the Excel Solver utility are given in cells B52:B59. The coefficients of variation of the interarrival times C_{aj} are computed in the same fashion, by satisfying the following constraints (see Equation 4-8):

$$C_{aj}^2 - p_{0j} C_{0j}^2 + \sum_{i=1}^n p_{ij} [q_{ij} (\rho_i^2 C_{pi}^2 + (1 - \rho_i^2) C_{ai}^2) + 1 - q_{ij}] = 0 \quad .$$

These equalities are entered in cells N39:N46 and the solution of the system is reported in cells D52:D59. Finally the estimated waiting time and flowtime per operation (respectively per job) are given in cells F52:G59 (respectively L52:M59). The average number of jobs in the queues is computed in cells N52:N59. The total expected waiting time and flowtime per job are entered in cells L61:M61.

4.5.2. The transition matrix

In section 4.2, the assumption was made that the number of tasks for every job is five. The number of possible routings for the flowshop and the jobshop was also computed. To construct the transition matrix q_{ij} it is necessary to aggregate all the different routings. As a consequence of the aggregation, the number of tasks per job can be different from five. For example, since the machines visited are based on probabilities, jobs in the flow shop could visit as few as 3 machines and as many as 6. However, on average five machines will be visited. The row and the column of the matrix that represent the outside world are called *arrival (Arr.)* and *departure (Dep.)*. Hereafter, the row and column numbers will be used to refer to the respective machine number. The matrices for the flowshop and the jobshop model are given in Table 3 and Table 4. In Table 3, the MH strategy is used whereas the BIC strategy is shown in Table 4. An explanation of how the values of the components were obtained is given next.

<i>From\to</i>	1	2	3	4	5	6	7	8	Dep.
Arr.	0	0	0	0	0	0	1	0	0
1	0	0.8	0.2	0	0	0	0	0	0
2	0	0	0.8	0.2	0	0	0	0	0
3	0	0	0	0.8	0.2	0	0	0	0
4	0	0	0	0	0.8	0.2	0	0	0
5	0	0	0	0	0	0.8	0	0	0.2
6	0	0	0	0	0	0	0	0	1
7	0.8	0.2	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	0	0

Table 3: Transition matrix for the flowshop, with the MH strategy

All the possible routings were listed in Table 2 for the flowshop model. The transition matrix for this particular model can be computed by counting, for each q_{ij} , the number of times machine i is followed immediately by machine j in the set of all possible routings. This number is then divided by the number of times machine i appears in the routings. As an example the computation of q_{12} is shown. Since the sequence 1-2 appears four times and the machine 1 appears five times, the value of q_{12} is equal to 4/5. In the same fashion, q_{13} is equal to 1/5.

For the MH strategy, all incoming jobs go to machine 7 directly, and therefore $q_{arrival,7}$ is equal to 1. (For the BIC strategy, only the bottleneck jobs start on machine 7. Since five routings out of six include the bottleneck machine, $q_{arrival,7}$ is equal to 5/6 and $q_{arrival,1}$ is equal to 1/6, since all the non-bottleneck jobs start on machine 1.)

<i>from \ to</i>	1	2	3	4	5	6	7	8	Dep.
Arr.	0.07	0.07	0.07	0	0.07	0.07	0.66	0	0
1	0	0.16	0.16	0.16	0.16	0.16	0	0	0.2
2	0.16	0	0.16	0.16	0.16	0.16	0	0	0.2
3	0.16	0.16	0	0.16	0.16	0.16	0	0	0.2
4	0.16	0.16	0.16	0	0.16	0.16	0	0	0.2
5	0.16	0.16	0.16	0.16	0	0.16	0	0	0.2
6	0.16	0.16	0.16	0.16	0.16	0	0	0	0.2
7	0.17	0.17	0.17	0.17	0.17	0.17	0	0	0
8	0	0	0	0	0	0	0	0	0

Table 4: Example of the transition matrix for the jobshop, with the BIC strategy

For the jobshop model, all components q_{ii} are equal to zero, since a machine cannot process the same job twice in a row. As every job has five tasks on average, the

probability of a job being completed and leaving is $1/5$. A job leaving machine i that does not exit the system can transit to any machine j with a probability equal to $0.8/5=0.16$.

For the MH strategy, once again, all incoming jobs go to machine 7, and therefore $q_{arrival,7}$ is equal to 1. For the BIC strategy, only the bottleneck jobs first go to the dummy machine. It is then necessary to compute the probability that a job does not go through the bottleneck. A job has its first operation on a non-bottleneck machine with probability $5/6$. Any other operation has a $4/5$ probability of visiting a non-bottleneck machine next, since it cannot be processed consecutively on the same machine. Since each job has five operations, a job skips the bottleneck with probability $5/6 * 4^4/5^4 = 0.34$. Therefore the probability of going from the arrival directly to a machine – except machine 4 – is given by $0.34/5 = 0.07$. The component $q_{arrival,7}$ is therefore given by $1 - 0.34 = 0.66$. Note that the proportion of jobs that go through a bottleneck machine is smaller for the jobshop than for the flowshop. Therefore the effect of the dummy machine for the BIC strategy will not be as important for the jobshop as for the flowshop.

4.6. Analytical Results

The spreadsheet model presented is used to compare the three different levels of bottleneck described in section 4.4. The mean processing time of the dummy machine is set to 0.2 or 0.85. When the processing time is short, the machine does not level out the variations in the interarrival times as much as when the processing time is long. By changing this processing time, the effect on waiting times in the system can be observed.

4.6.1. The flowshop

All the spreadsheet results for the flowshop are given in Appendix1. A summary of the results is given in Table 5 and in Table 6. First it is important to know what the influence of the bottleneck on the flowtime is. As can be expected, the bottleneck increases the mean flowtime. In particular, the queue of the bottleneck becomes much longer. The difference in the flowtimes between the balanced shop and a shop with a light bottleneck is relatively small. There is a bigger difference between the shop with a light bottleneck and one with a severe one, as shown in Figure 3 and Figure 4. At the same time, the coefficient of variation of the interarrival times decreases for the machine following the bottleneck. As a matter of fact, the bottleneck regulates the variation in the interarrival time of the following machine.

Dummy machine proc. time	B/N level	MH strategy			BIC strategy		
		No	Light	Severe	No	Light	Severe
0.2	Release	0.029	0.029	0.029	0.019	0.019	0.019
	Flowtime	19.893	20.562	22.278	19.959	20.623	22.288
	Leadtime	19.922	20.591	22.255	19.978	20.642	22.307
0.85	Release	7.225	7.225	7.225	1.309	1.309	1.309
	Flowtime	17.395	18.249	19.984	18.599	19.563	21.065
	Leadtime	24.620	25.474	27.209	19.908	20.672	22.374

Table 5: Times in the flowshop

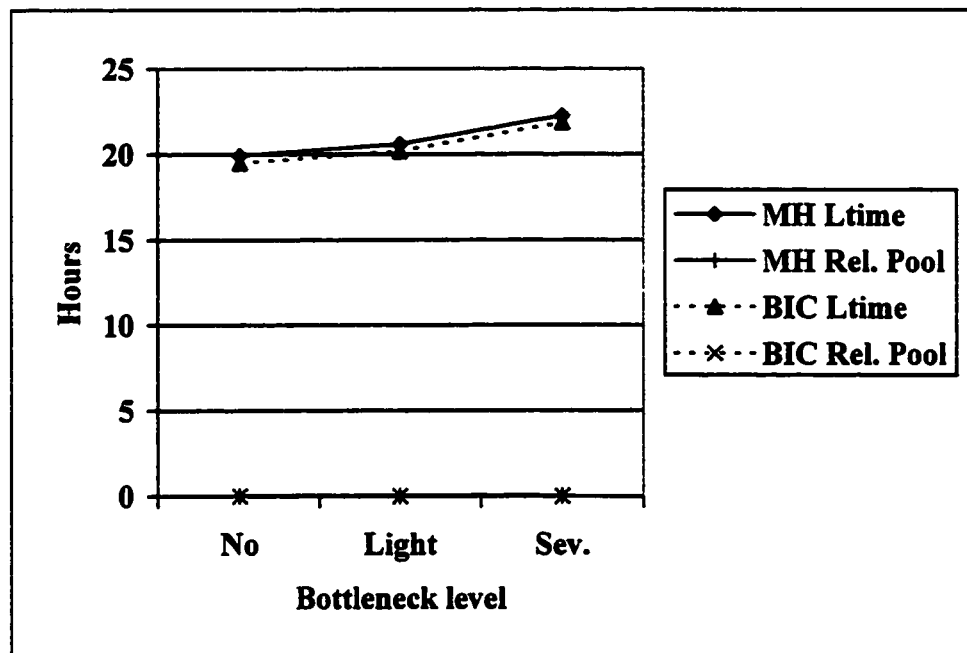


Figure 3: Times in the flowshop when dummy machine processing time is 0.2

The queuing model shows slight differences in performance between the two strategies. For the MH strategy, the coefficients of variation of the interarrival time at the first few machines decrease when the processing time of the dummy machine changes from 0.2 to 0.85. This can be observed in Table 6. The length of the queue at the dummy machine increases from 0.032 to 8.028 when the dummy machine processing time changes from 0.2 to 0.85. At the same time, the time in the shop is reduced. However, the reduction gets smaller as the level of the bottleneck increases (see Table 5). Note that in any case, the leadtime (the sum of the waiting time at the dummy machine and the time in the shop) goes up with the increase of the dummy machine processing time.

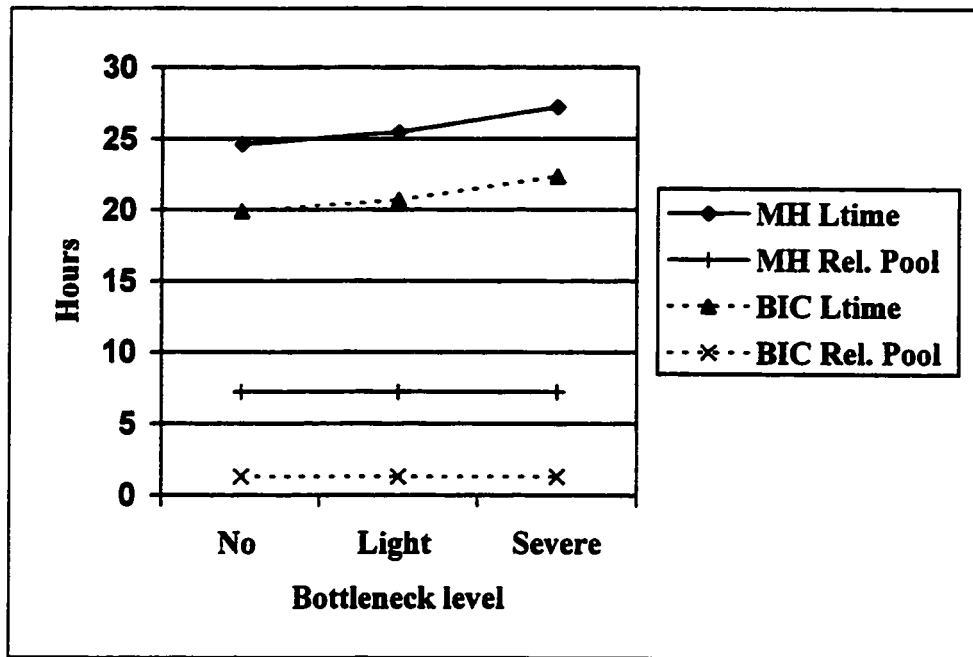


Figure 4: Times in the flowshop when dummy machine processing time is 0.85

For the BIC strategy, the dummy machine does not have a great influence on the shop. Changing the processing time from 0.2 to 0.85 affects the flowtimes only slightly (see Table 5, Figure 3 and Figure 4). The length of the queue at the dummy machine increases from 0.018 to 1.212 when the dummy machine processing time increases from 0.2 to 0.85. The time in the shop and the coefficients of variation of the interarrival times at the first three machines are slightly reduced, as shown in Table 6. Also note that when the shop is balanced, the leadtime is shorter when the utilization of the dummy machine is high. When the shop is not balanced, the leadtime increases only slightly.

When the dummy machine utilization is low, the MH strategy performs slightly better, as far as the average leadtime is concerned. When the utilization of the dummy

machine is high, the BIC strategy performs better. However, the time in the shop is shorter and the coefficients of variation of the interarrival times are smaller for the MH strategy than for the BIC strategy.

CV_a		MH strategy with severe B/N		BIC strategy with severe B/N	
Mach.	Dummy m. proc. time	0.2	0.85	0.2	0.85
1		0.959	0.257	0.978	0.604
2		0.632	0.491	0.635	0.552
3		0.558	0.529	0.559	0.542
4		0.543	0.537	0.543	0.54
5		0.512	0.511	0.512	0.511
6		0.533	0.533	0.533	0.533
7		1.000	1.000	1.000	1.000

Table 6: Coefficients of variation of the interarrival times for the flowshop

4.6.2. The jobshop

The spreadsheet results for the jobshop are reported in Appendix 2. The results are given only for the level 3 of the bottleneck, since the introduction of a bottleneck increases the flowtime in the same way as observed in the flowshop model.

The effects of the dummy machine on the shop are relatively limited. For the MH strategy, the time spent in the shop is reduced by less than one hour, even when the dummy machine processing time is high. This is shown in Table 7. In fact, the coefficients of variation of the interarrival times at any machine remain close to one,

regardless of the dummy machine processing time (see Table 8). It is therefore of little use to control the arrivals in a jobshop.

Dummy machine proc. time	Times in the shop	MH strategy with severe B/N	BIC strategy with severe B/N
0.2	Release	0.029	0.011
	Flowtime	28.026	28.063
	Leadtime	28.055	28.074
0.85	Release	7.225	0462
	Flowtime	27.431	27.829
	Leadtime	34.656	28.291

Table 7: Times in the jobshop

For the BIC strategy, the role of the dummy machine is also minimal. The time spent in queue at the dummy machine is short, even when the processing time of the dummy machine is 0.85.

CV_i		MH strategy with a severe b/n		BIC strategy with a severe b/n	
Mach.	Dummy mach. Proc. time	0.2	0.85	0.2	0.85
1		0.921	0.892	0.923	0.916
2		0.921	0.892	0.923	0.916
3		0.921	0.892	0.923	0.916
4		0.924	0.895	0.924	0.906
5		0.921	0.892	0.923	0.916
6		0.921	0.892	0.923	0.916
7		1.000	1.000	1.000	1.000

Table 8: Coefficients of variation of the interarrival times in the jobshop

The MH strategy performs better regarding the leadtime, when the dummy machine processing time is low. If this processing time is high, the BIC strategy performs better. However, neither of the two is good at reducing the variations in the shop.

4.6.3. Comparison of the two shops

The flowtime for the jobshop is longer than for the flowshop. This is consistent with previous findings. The flowtime is shorter in a shop with a unidirectional flow, unless the coefficient of variation of the processing times is higher than one (Buzacott and Shanthikumar, 1993).

The control of the arrivals does not have the same impact on the two shops. For the flowshop, it is important to control all the arrivals (MH strategy) to reduce the length of the queues in the shop, and hence the time spent in the shop. For the jobshop, it is of little use to control the arrivals, since the jobs go randomly from one machine to another. It is therefore more important to control how the shop is loaded before releasing jobs.

4.6.4. Conclusion

The queuing model developed in this section shows that the leadtime increases when workload is shifted from the shop to the release pool. The same phenomenon has been observed in many studies (see chapter 2.2). The queuing model shows that the BIC strategy performs better in terms of the average leadtime. However, the validity of this model is limited since it controls the arrivals onto the shop, instead of the workload.

Moreover, it aggregates all the jobs and, in particular, neglects the differences between bottleneck and non-bottleneck jobs.

5. SIMAN model

Simulation provides an excellent tool to compare the relative performance of the two order release strategies. In this chapter a simulation model using SIMAN V software (Pegden, Shannon and Sadowski, 1995) is described. The model and experiment files are given in appendices 3 and 4. The following discussion assumes the reader is acquainted with the SIMAN simulation language. However, only the operation of the program is described in this chapter. The general framework for the model is given in Chapter 3, and the parameters and factors of the experimental plan are presented in Chapter 6. Therefore the reading of this chapter is not essential for the comprehension of the following chapters and the reader who is not familiar with SIMAN may want to skip it.

5.1. Summary of the model file

The numbers in brackets on the model and experiment files given in appendices 3 and 4 help to point out the different features of the model. They will be referred to throughout the discussion.

5.1.1. Model parameters [10]

The various parameters enable the 6 machines shop to be configured in many ways. Adjustment of these parameters allows flexibility in experimentation. All the parameters and their use are listed in Table 9. It should be emphasized that the parameter UL does not give the real utilization level of the machine, since every machine processes not all the jobs. The real utilization level can be obtained by multiplying the parameter UL by *arrival rate*average number of tasks per job/number of machines*. Therefore the UL parameter is used to set the desired utilization level of a machine and can be higher than one. This parameter is also used to differentiate the utilization of the bottleneck from the other machines. Note that this could be done directly by modifying the MPT parameter.

1	Marr	0.9	Mean interarrival time
2	NbT	0,1,0,2,0,3,0.33,4,0.67,5,1,6	Number of tasks distribution function
3	R1	0,1,,2,2,0.4,3,0.6,4,0.8,5,1,6,1,7	R1-Rout: probability transition matrix for the different jobs; in SIMAN the probability are given as cumulative probabilities.
4	R2	0.2,1,0.2,2,0.4,3,0.6,4,0.8,5,1,6,1,7	
5	R3	0.2,1,0.4,2,0.4,3,0.6,4,0.8,5,1,6,1,7	
6	R4	0.2,1,0.4,2,0.6,3,0.6,4,,8,5,1,6,1,7	
7	R5	0.2,1,0.4,2,0.6,3,0.8,4,0.8,5,1,6,1,7	
8	R6	0.2,1,0.4,2,0.6,3,0.8,4,1,5,1,6,1,7	
9	Rout	1,1,1,2,1,3,1,4,1,5,1,6,1,7	Prob transition vector that a job leaves the system
10	MPT	1,1,1,1,1,1	Mean processing time on each machine before UL is decided
11	CVP	0.5,0.5,0.5,0.5,0.5,0.5	Coeff. of Var. of the proc. Time for each machine
12	k	2,2,2,2,2,2	Erlang distribution parameter
13	PTD	1	Processing time distr. (1= Erlang, 2=Normal)
14	UL	0.93,0.93,0.93,1.05,0.93,0.93	Utilization level for each machine
15	PPW	6	k parameter for the due date setting rule
16	DDSR	1	0 if NOP, 1 if TWK, 2 if PPW
17	DR	1	Choice of the dispatch rule
18	RS	1	Strategy chosen (1= MH strat., 2=BIC strategy)
19	MaxHours	75	Trigger level
20	MWT	15	SPTT time truncation
21	FO	1	=1 if flow =0 if jobshop
22	BNM	4	bottleneck machine
23	PBN	0	if the bottleneck priority rule (BNPR) is used then equal to 1; 0 otherwise

Table 9: Model parameters

5.1.2. Random Numbers [12]

Multiple independent replications are run at each combination of experimental settings. Common random numbers (CRN) are used as a variance reduction technique. This approach helps to reduce the effect of within-group variance when comparing multiple systems. The 'common' option further helps facilitate using the same sets of random numbers across comparable replications.

Different streams are used for each different requirement based on random numbers (e.g. interarrival times, processing times, etc.).

5.1.3. Creation of a new job [1], [3]

Each time a new job is created, its attributes are defined. First, the number of tasks is decided. If any kind of shop but a flowshop is simulated, the exact number of tasks is assigned sequentially to each job. On the contrary, if the user wants to study a flowshop model, then six tasks (one on each machine) are assigned to the jobs (some of them will be deleted later). The processing times and routings are defined next. At the same time, whether or not the job requires the bottleneck resource is determined. If the job does require a bottleneck resource, the attribute ThruBN will be changed from 0 to a positive value. At block [3] the due date is computed in accordance to the due date setting rule chosen.

5.1.4. Flowshop model [2]

If the user wants to simulate a flowshop, then six tasks have been assigned to each job. If the attribute number of tasks for a particular job has been set to less than six, then some of its operations are selected randomly to be removed. The remaining processing time is corrected accordingly. If some bottleneck jobs become non-bottleneck jobs, their attribute `thruBN` is set back to 0.

5.1.5. Release of the job to the shop [4]

If there is no input control, the job is released directly to the shop. Otherwise the value of the Work-In-Process variable or BNQ Length variable, which keeps track of the Work En Route to the bottleneck, is checked. If the shop is currently too heavily loaded, the job is diverted to an order input pool. Every time an operation is started on a machine, a new job is released, if possible (see next section).

5.1.6. Arrival of jobs to machines [5], [6], [8]

Once a job has been released, it must transit from one machine to another according to its specified routing. When the job arrives at a particular machine, it is added to the queue if the machine is busy. If the machine is idle, the machine is turned on, and the job is started.

Before each operation is started, the Work-In-Process and BNQ Length variables

are adjusted. The Work-In-Process and BNQ variables at a given time do not include the tasks in process. If the variable of interest (either WIP or BNQ Length) is below the critical level, the program allows the release of new jobs at block [8]. When the operation of a particular job is completed on machine i , the job is sent to the next machine. At the same time a new job is loaded on machine i unless the queue is empty.

5.1.7. Management of the queues [7]

When a resource becomes available, the model searches the queue for the job with the highest priority, as dictated by the dispatch rule. The optional BNPR, which gives priority to jobs that will pass through a bottleneck resource, is included in the computation of priorities. When it is activated, a high weight priority is given to jobs moving toward the bottleneck. This avoids the need for separate queues and simplifies the model.

5.1.8. Collection of statistics [9], [9A]

The flowtime, flowtime per operation, leadtime, mean lateness and mean tardiness are collected for every job completed. The number of tardy jobs and the total number of completed jobs (or throughput) are also of interest. As well, the WIP (in hours), the aggregate utilization of the shop, the average number of jobs in the shop and the average number of jobs in the system are saved. These latter measures are time-

dependent statistics. For example, utilization is the average percent of time that machines in the shop are busy.

Seven parameters are kept track of to define the characteristics of the experiment run. These are also written out to an external file, along with the summary performance data at the end of each replication. These parameters are as follows:

1. the replication number,
2. the type of routing,
3. the release strategy chosen,
4. the level of the bottleneck,
5. the absence or presence of the priority rule,
6. the dispatch rule chosen, and
7. the coefficient of variation of the processing time.

These statistics are saved in a free format file in order to make analysis using statistical software convenient.

5.2. *Validation of the model*

Several other statistics are collected to verify that the model is valid (see [13]). In particular, the mean processing times, the processing time coefficients of variation, the utilization level of the machines, the number of jobs in the system and the length of the queues have been carefully checked. These statistics are not saved in the free format file.

6. The production environment

The general framework presented in Chapter 3 is now narrowed to establish a feasible experimental plan. In this chapter the values of the fixed parameters are discussed first. The factors involved in the experimental plan are then presented. The values of the parameters and the factors have been chosen to match as closely as possible the values used in the queuing model. In the last section, the data collection applied is described.

6.1. *Parameter selection*

The model can be used to simulate many different shop and work load configurations. This section indicates the settings chosen for experimentation, based on the study objectives and on preliminary simulation runs.

The arrival of the jobs is modeled as a Poisson process, with a mean interarrival time of 0.9. The processing time is represented by a 2-Erlang distribution shifted from the origin so that the mean is one and the coefficient of variation is equal to 0.5. Thus the processing time is the sum of a constant part equal to $(1-1.414*0.5)$ and a variable drawn from a 2-Erlang distribution with mean equal to $0.5/1.414$ (see Equation 3-3 and Equation 3-4). The coefficient of variation is consistent with the levels observed in

previous research on dispatching and ORR. This can be considered to provide an “average” amount of variability. The number of operations for each job is uniformly distributed between four and six, and the jobs visit all machines with equal probabilities.

The bottleneck resource is machine number 4. As already stated, it differs from the other machines in that it may have a larger mean processing time. For the jobshop model, the position of the bottleneck does not matter since routings are random. For a flowshop, its position will influence the workflow. The further upstream the bottleneck is placed, the more downstream variability will be reduced. This is the case only because the coefficient of variation of the processing time is smaller than the coefficient of variation of the interarrival times (see Equation 4-8). Under this condition, highly utilized machines tend to moderate the variation of the arrivals to downstream machine. It was therefore decided to place the bottleneck machine near the middle of the flow line.

It is better to have a high average machine utilization in order to obtain significant differences between the two strategies. If there is a lot of excess capacity any order release strategy will perform reasonably well. Hence, the average shop utilization level was set to 88%. This utilization level is low enough so that a large enough difference in the mean processing times between the bottleneck machine and the other machines can be maintained without having the bottleneck utilization exceed 95%. At the same time, it is high enough so that significant queues form and performance differences can be observed.

6.2. *Experimental plan*

The experiments are designed so that both release strategies can be compared in two different kinds of shop. The first configuration is a flowshop and the second is a jobshop. The flowshop and jobshop settings for the routing factor are part of a full factorial experimental design. However, the results are treated separately in much of the initial statistical analysis. This simplifies analysis and makes the behavior of the system more transparent with respect to other factors and interactions.

6.2.1. Experimental factors

Four factors are varied under each of the routing assumptions. The factors are summarized with the number of levels for each in Table 10. The first factor identifies the release mechanism from the order pool. The Maximum Hours strategy (MH) described in section 3.3.1 is to be compared with the Bottleneck Input Control (BIC) strategy described in section 3.3.2.

The severity of the bottleneck relative to the other machine utilizations is the second factor. This is defined by the utilization level (UL) parameter. The three following levels are taken into consideration:

Level 1. $UL=0.95$ for all machines.

Level 2.(Light bottleneck). UL is set at 0.94 for machines 1,2,3,5,6 and 1 for machine 4.

Level 3.(Severe bottleneck). UL is set at 0.935 for machines 1,2,3,5,6 and 1.025 for machine 4.

As mentioned previously, UL must be multiplied by $(5/6) * \text{arrival rate}$ to give the actual utilization level of the machine.

Factors	Levels
Release strategies (abbreviated RS)	1. MH 2. BIC
Level of the bottleneck (abbreviated B/N)	1. No bottleneck 2. Light bottleneck 3. Severe bottleneck
Bottleneck Priority rule (abbreviated BNPR)	1. No BNPR 2. BNPR
Dispatch rule (abbreviated DR)	1. FCFS 2. SPTT

Table 10: Experimental factors

At the first level there is no real bottleneck since all machines have equal utilization. However, in order to maintain control of releases when the bottleneck strategy is used, machine number 4 is still considered the bottleneck. Although with a balanced shop load the BIC strategy is likely to be a poorer performer, this particular setting enables the behavior of the BIC strategy when the bottleneck is almost non existent to be predicted. At the third level, with a mean interarrival time of 0.9, the utilization level of machine 4 is equal to 95% $(1.025/0.9 * 5/6)$. Since the bottleneck machine is almost fully utilized, more congestion would be expected at this particular level.

The third factor differentiates the shop simulated with the BNPR (discussed in

section 3.4) from the ones simulated without. With this rule the jobs that have an upcoming operation on the bottleneck machine are processed before any non-bottleneck jobs waiting in the queue.

The last factor relates to the dispatch rules. Although six different dispatch rules are implemented in the simulation model, only two rules are included in the experimental plan. This is done for two reasons. First, the size of the experimental plan has to be reasonable. Second, previous studies with order review/release show that the dispatch rule has a relatively small influence on shop performance when a release strategy is used (Roderick, Phillips and Hogg, 1992).

The first rule chosen is FCFS since it is not influenced by the job and the shop characteristics and therefore allows for testing the release strategy without complicating interactions. The second rule chosen is SPTT. When this rule is used, the job with the shortest operation in the queue is processed first, unless there are other jobs that have stayed in the queue for more than 15 hours. In the latter case, the jobs are processed on a first-come-first-served (FCFS) basis. This rule performs well under many shop conditions, although it has been argued that the tardiness associated with jobs having long processing times is high. Due-date dependent dispatching rules are avoided in the experimental plan because of due-date tightness interaction effects. Moreover when the due dates are tight, the SPTT is likely to produce better results than a due-date dependent dispatch rule.

6.2.1.1 Due date settings

The due-date setting method and planned leadtimes are also of concern. These are considered apart, since they influence only the tardiness measures when due date independent dispatch is used. In other words, the due-date rule and tightness settings are not considered experimental factors. In section 3.1, different due-date setting rules were proposed. Due-dates settings are not considered an experimental factor, since delivery performance is not of primary concern. However, tardiness measures are looked at separately at a secondary level of analysis. To compute tardiness measures, the PPW and TWK rules are both used. Three different levels of tightness are assumed. For the PPW rule the parameter k_{PPW} is set to 7, 9 and 11. For the TWK rule, the parameter k_{TWK} is set to 8.368, 10.474 and 12.579 so that the mean planned lead times are comparable under both due date setting rules. This results in planned leadtimes of 39.5, 49.5 and 59.5 respectively. Therefore six different sets of delivery dates are computed for each combination of factor settings.

6.3. Data collection

In this section the details of the data collection during simulations are given. In the following sections, it is assumed that the trigger levels for the order release strategies are known and fixed. The choice of this value for each combination of settings is explained in the next chapter.

6.3.1. Variance reduction technique

Multiple independent replications are run at each combination of experimental settings. Common random numbers (CRN) are used as a variance reduction technique. This approach helps to reduce the effect of within group variance when comparing multiple systems.

As stated in Law and Kelton (1991), the variance of the difference D between two variables X_a and X_b can be expressed as $Var(D) = Var(X_a) + Var(X_b) - 2Cov(X_a, X_b)$. Suppose that several simulations of two shops configurations a and b are run. Let X_{aj} and X_{bj} be the observations of variable X for shops a and b at the end of the j th replication. If the two alternative systems are simulated with different random streams, the observations X_{aj} and X_{bj} are independent and the covariance between them is zero. However, if identical random numbers are used for each replication, then X_{aj} and X_{bj} are correlated. If the two systems react similarly to an identical change in random input streams this correlation is *positive*. Hence the variance of the difference $D_j = X_{aj} - X_{bj}$ is reduced, as can be seen from the above formula.

Different streams are used for each different requirement based on random numbers (e.g. interarrival times, processing times, etc.). The different shop configurations will probably react similarly to a change in the input streams. It is therefore likely that the variance of the results will decrease by applying the CRN variance reduction technique.

6.3.2. Warm-up period

The shop is assumed to be empty at the beginning of the simulation. The observations collected at the end of a run are valid only if they are gathered after the shop has reached steady-state conditions. In order to determine the length of the warm-up period, data was gathered during a preliminary simulation run. A graph of the moving average for the different variables enables making an estimate of when the steady state is reached. If some variables are highly correlated, it is not necessary to generate a graph for each of them. Since the leadtime and the tardiness measures need a longer time to become stable and are highly correlated, the graphs of the moving average of one of these measures are sufficient to determine the warm-up period. The time to steady-state condition was visually determined.

A pilot run is executed for each combination of settings. Based on the observations of this run, graphs of the moving average over 50 observations of the leadtime measure are drawn. It turns out that all the graphs are very similar under the same settings. The longest transient period is 10,000 hours and occurs when the MH strategy is applied to the jobshop model with a severe bottleneck. Since common random numbers are used (see section 6.3.1), the same transient period is used for all the combination of settings and for both the flowshop and jobshop. In such a way, all statistics are collected from roughly the same set of jobs.

6.3.3. Run length

The run length after the warm-up period must be long enough so that the data gathered does not depend on the values of the input streams. To ensure that the replication length is appropriate, a new simulation is run. After the steady state has been reached, data is gathered again until the end of the simulation. A correlogram of the successive observations is constructed for every variable. In this way the longest period of time necessary until two observations of the same variable are no longer positively correlated can be determined. The run length should be at least ten times as much as this longest period, as suggested in Pegden, Shannon and Sadowski (1995). This run length gives reasonably tight confidence intervals when a sufficient number (e.g. 10 or 20) of independent replications are performed.

Since the observations within a run are highly correlated, a long run is necessary to obtain satisfactory results. A second pilot run of 15,000 hours has been generated for all the settings, with a warm-up period of 10,000 hours. A graph representing the correlation between successive measures is constructed for the same measures as previously. The longest positive autocorrelation arises between 1,600 successive jobs, and again is found to be in the jobshop for the actual leadtime measure. As suggested in Pegden, Shannon and Sadowski (1995), the run length is chosen so that the system generates at least 16,000 jobs. Since the arrival rate is higher than one, more than one job is generated on average per hour. Therefore a run length of 16,000 hours is sufficient.

6.3.4. Number of replications

Data generated from a stochastic simulation is stochastic. Hence several replications must be run in order to obtain sufficient samples from which valid conclusions can be drawn. The replication/deletion approach has been chosen from among the different alternatives to generate independent output samples (see Law and Kelton, 1991). For each simulation replication, the response is the mean of all the measures collected during the replication, after the transient phase is eliminated. One exception is the throughput, which is the sum of all the jobs completed during the simulation.

The number of replications is set to 20. This number seems reasonable to obtain sufficiently tight confidence intervals for the leadtime and tardiness measures.

7. Selection of Order Release Parameters

The previous chapter described the factors and parameters of the experimental plan. In the first part of this chapter, the relationship between the WIP and the throughput is described. The Maximum Hours (MH) strategy delays the arrival of new jobs onto the shop floor when the WIP is above a certain level. In the same fashion, the Bottleneck Input Control (BIC) strategy regulates the Work En Route to the bottleneck. Before running experiments, (see section 6.3) it is necessary to determine at which level of WIP or Work En Route to the bottleneck a new release should be triggered. In other words, the order release mechanism must be specified. In the second part of this chapter, appropriate trigger levels for the experimental plan are chosen. To reduce the size of the experiments, the trigger levels are set to a single value for each combination of settings.

7.1. *Operating curves*

The trigger levels correspond to the level of WIP or Work En Route to the bottleneck at which orders are allowed onto the shop floor. Some insight into the behavior of both strategies with respect to a change in the trigger level must be obtained prior to running the experimental plan. The mean WIP and the throughput will grow monotonically with the trigger levels, whereas the leadtime will decrease. The relationship between the mean WIP and the throughput for each different system can be

obtained through plots called operating curves. They will help in deciding on the values of the trigger levels to be used the experimental plan, as explained in section 7.2.

Several simulations are run to generate points on the operating curves. In the next three sections, the different phases of constructing the curves are detailed. First some general comments are presented, then the warm-up period and run length used in developing the operating curves are discussed and finally some comments on the creation of the curves are given.

7.1.1. Preliminaries

In order to find a range of acceptable values for the trigger levels, 5 simulations are run for each combination of factors over a wide range of trigger levels. The parameter values established in section 6.1 are used. For this preliminary search, the SIMAN simulation is run once but set at 50 replications. The trigger level is increased after every set of five replications. Therefore one run represents results based on ten different trigger levels, each with five independent replications.

These results have also been compared to a simulation without input control. In the latter case shorter leadtimes are observed. However, a very high level of WIP is necessary to obtain these short leadtimes. This is consistent with the results obtained by Baker (1984). Results of these preliminary experiments are not included in later analysis and therefore are not presented.

7.1.2. Simulation warm-up and run length

To construct the operating curves, only the WIP and throughput variables are necessary. (Recall that the WIP is computed as the sum of the remaining processing times of all the jobs on the shop floor). Since these two variables are highly correlated with the flowtime per operation, the latter measure is used to estimate the warm-up period and run length. As mentioned earlier, the throughput and the WIP vary monotonically with the trigger level. However the more WIP is allowed into the shop, the longer the queues will be on average. As a consequence the variation in the flowtime increases, since the amount of work will be more variable over time. Therefore the warm-up period and the run length have to be longer when a shop with a very high trigger level is simulated. The methods described in sections 6.3.2 and 6.3.3 are used to determine the warm-up period and the run length.

The warm-up period and run length do not have to be the same for all combinations of settings. However, it is easier to find a worst case to establish a single warm-up period and run length suitable for all the combinations of settings. Also, having the same initialization period means the CRN variance reduction technique (see section 6.3.1) will function better. The longest warm-up period and run length are required when the B/N factor is at level 3, there is no BNPR and the FCFS dispatch rule is used. Table 11 gives the values of the trigger values in the worst case scenarios for the flowshop and the jobshop. These trigger levels are higher than the ones used to build the curves.

The graphs of the moving average over 50 successive observations for the worst case scenarios are given in Appendix 5. The warm-up period is chosen to be 1,500 hours.

Note that the warm-up period is chosen to be as short as possible, since many replications (more than 7,000) have to be run to determine the operating curves. To establish the run length, a second pilot run is made, with a warm-up period of 1,500 hours. On the basis of the correlograms of the flowtime per operation (shown in Appendix 6) which show a positive auto-correlation over a maximum of 500 successive jobs, the run length is set to 5,000 hours.

Shop \ Release strategy	MH strategy	BIC strategy
Flowshop	80 hours	16 hours
Jobshop	87 hours	16 hours

Table 11: Trigger levels used to determine the warm-up period and the run length

7.1.3. Creation of the curves

Ten replications are generated by the replication/deletion approach (see Law and Kelton, 1991) for every combination of the factors and for 15 to 25 different trigger values. All the statistical data identified in Section 5.1.8 is collected for each of the ten replications. A Visual Basic macro within an Excel spreadsheet allows the mean of the WIP and the throughput over the ten replications to be computed. This approach also facilitates saving these values in a text file. Finally, operating curves, showing the relation between the WIP and the throughput, are drawn using MINITAB (Minitab Inc., 1985). For comparison purposes the curves for both order release strategies are drawn on

the same graph. One such graph is shown in Figure 5. All the other graphs are included in Appendices 7 and 8. The small squares represent points of the curve for the MH strategy, whereas the crosses indicate points for the BIC strategy. In the remaining analysis a graph is referred to by the numbers given in its title. The first number in the title represents the level of the bottleneck, the second the absence (1) or presence (2) of BNPR, the third the FCFS (1) or SPTT (2) dispatch rule (See Table 10).

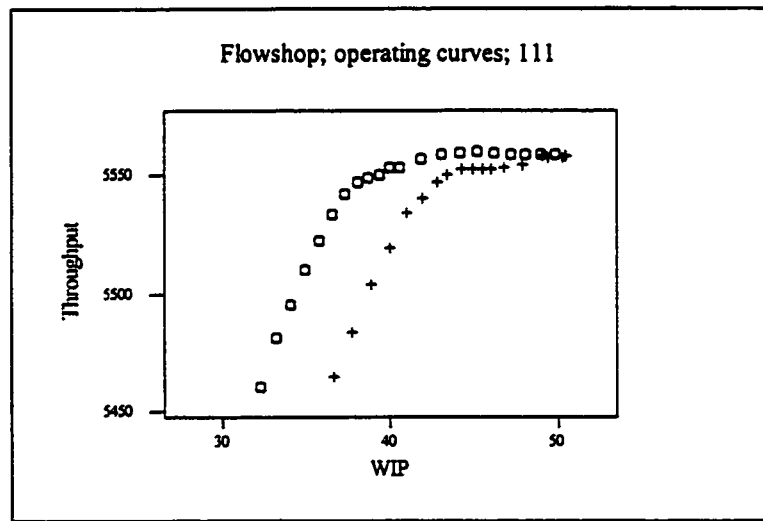


Figure 5: Operating Curve for balanced flowshop, no BNPR, FCFS

7.1.4. Comments on the operating curves

The data for the curves was collected over 5000 hours, with an arrival rate of $1/0.9$. By Little's Law (Askin, Standridge, 1993), the throughput per time unit generated by a shop with or without input control should be equal to $1/0.9$. Therefore the throughput at the end of the replication should theoretically be equal to 5556 jobs. Given that the observations are collected over a finite period of time, and for only ten replications, the throughput observed is sometimes higher than 5556.

The graphs of the individual replications (not shown in this thesis) indicate that the variation between the different sample observations is not too high, meaning the confidence interval is fairly tight. Moreover, they are good indicators of the superiority or inferiority of the performance of one release strategy over the other despite the variations in outputs. The results also confirm that the use of common random numbers (see section 6.3.1) produces more accurate estimates, since the response variables of the different systems increase or decrease similarly over paired replications.

The same increments are used to increase the trigger levels along the curve, except at its extremity. The graphs show, as expected, that the increase in throughput is not linear with the mean WIP. More surprising, however, is the fact that for the BIC strategy, there can be a dramatic variation from one trigger level to the next, especially when BNPR is present. As a matter of fact, BNPR allows the bottleneck jobs to go quickly through the shop. Therefore a shorter queue is necessary to produce the same throughput. As a consequence, when the trigger level is lowered, the percentage of reduction of the queue is not the same when BNPR is used as when it is not. This point needs to be considered since a slight reduction of the amount of Work En Route to the bottleneck machine may cause starvation.

7.1.4.1 The flowshop model

All the curves generated for the different flowshop configurations are given in Appendix 7. As mentioned earlier, the graphs are referred to by the numbers that appear

in their title. Recall that points of the operating curve for the MH strategy (respectively BIC strategy) are represented by squares (respectively crosses).

The graphs 111, 211 and 311 in Figure 5, Figure 6 and Figure 7 show that a change in the level of the bottleneck modifies the performance of the two strategies, but not in the same proportion. The graphs of the operating curves are very similar when there is no bottleneck and when the bottleneck is light. However, when the bottleneck becomes severe, the effectiveness of the MH strategy decreases more than the one of the BIC strategy. Part of the success of the BIC strategy depends on the existence of a strong bottleneck in the shop, as suggested by Morton (1993).

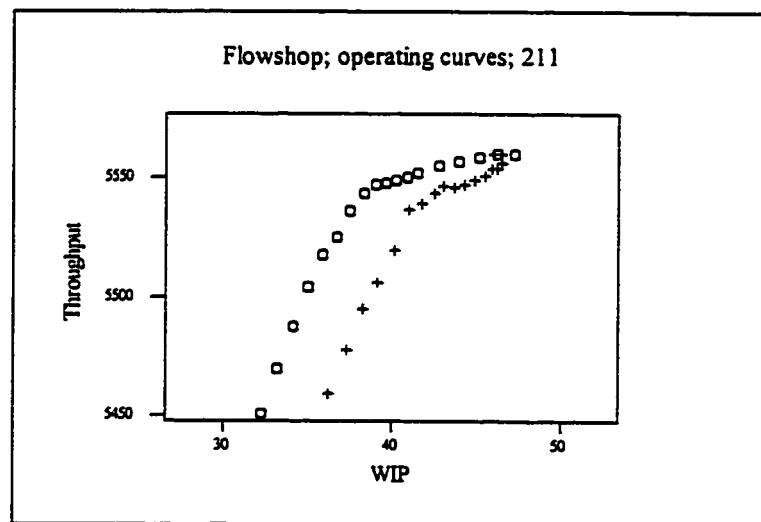


Figure 6: Operating curve for a flowshop with a light b/n, no BNPR, FCFS

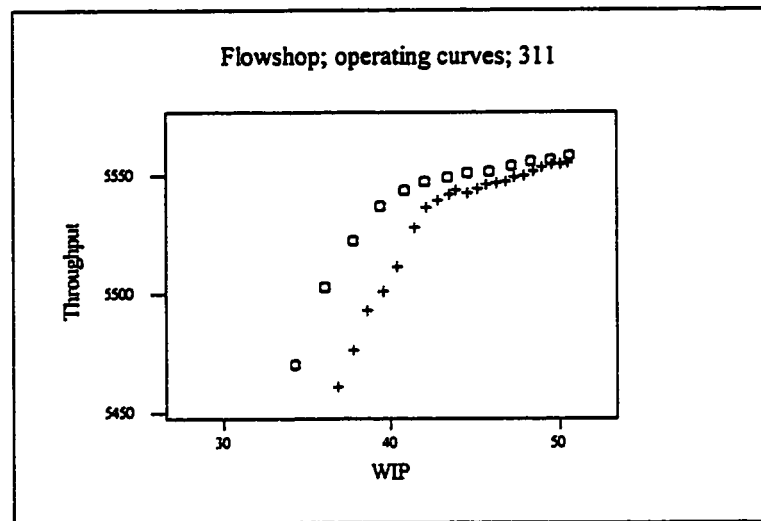


Figure 7: Operating curve for a flowshop with severe b/n, no BNPR, FCFS

The introduction of the BNPR is beneficial for both strategies, though the results obtained for the BIC strategy improve more. This is not surprising since this rule has been introduced to complement the Bottleneck Input Control (BIC) strategy. What is more surprising, though, is that BNPR reduces the ratio WIP over throughput even when there is no bottleneck machine (see graphs 111 and 121 in Figure 5 and Figure 8 for example). In this case, the bottleneck jobs are going through the shop faster, but at the expense of the non-bottleneck jobs. Since in this particular case, the latter have the same mean total processing time as the bottleneck jobs, leadtime variance may be increased, at least for the MH strategy. Note that the leadtime measures will be considered later.

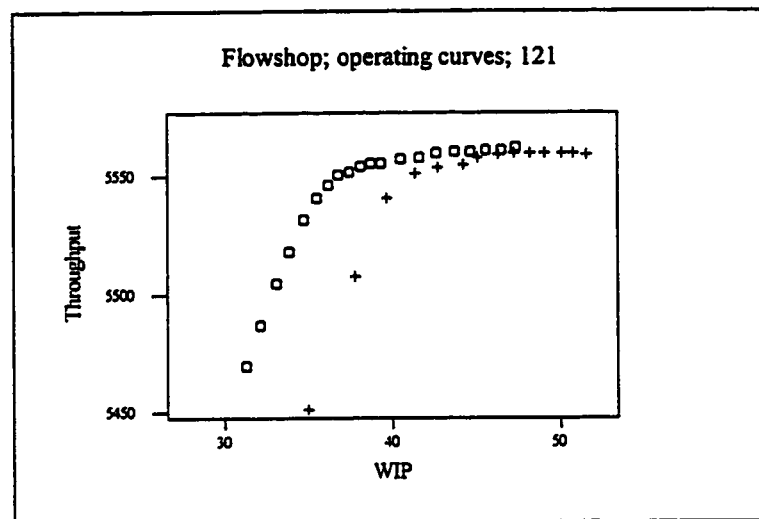


Figure 8: Operating curve for a balanced flowshop, BNPR and FCFS

When comparing dispatch rules, it can be seen that the SPTT dispatch rule allows the shop to produce the same throughput with less WIP than FCFS. The combination of the SPTT rule with the BNPR causes the WIP to be higher than when the SPTT rule is used alone (compare graphs 112 and 122 in Figure 9 and Figure 10). This is the result of competition between the dispatch rule and the bottleneck priority rule. All the jobs follow the same flow pattern and both rules aim at giving preference to selected jobs for processing next on the machine. However, the jobs chosen are not the same and the bottleneck rule makes the performance of the SPTT rule deteriorate. Note that this “competition” disappears as the bottleneck becomes more important. With a strong bottleneck, BNPR seems more appropriate, at least when high throughputs are considered.

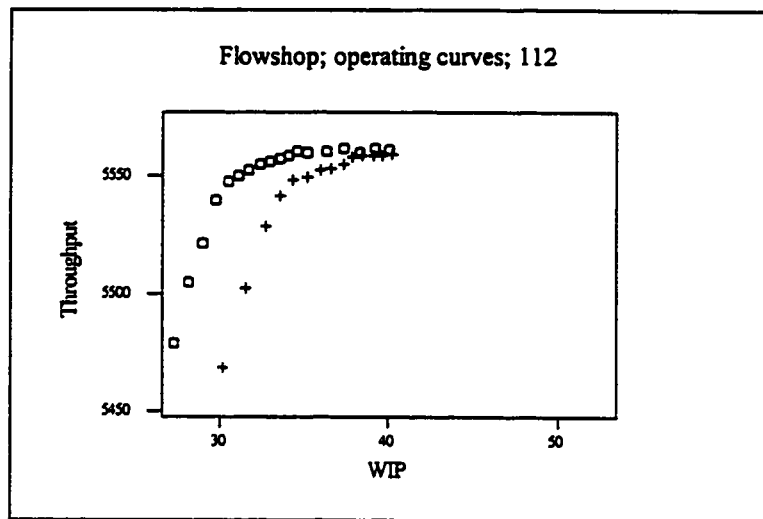


Figure 9: Operating curve for a balanced flowshop with no BNPR and SPTT

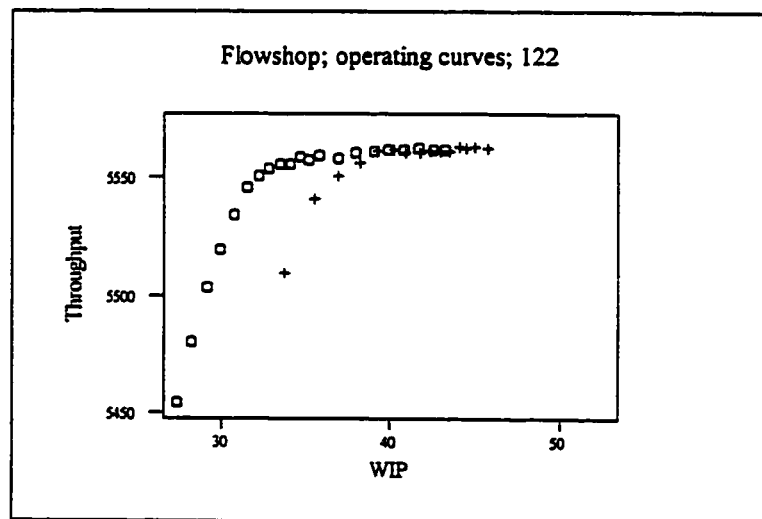


Figure 10: Operating curve for a balanced flowshop with BNPR and SPTT

7.1.4.2 *The jobshop model*

The curves for the jobshop model are given in Appendix 8. The use of the order release strategies does not have the same effects in the jobshop as in the flowshop. In the jobshop model the BIC strategy outperforms the MH strategy most of the time, at least when high throughputs are considered. The BIC strategy is very robust, since the curve stays approximately the same for the three different levels of bottleneck, as shown in the graphs 111, 211 and 311 in Figure 11, Figure 12 and Figure 13. The introduction of the BNPR makes the BIC strategy even more powerful, especially when there is a bottleneck (see graph 321 in Figure 14). In this case the BIC strategy can achieve a high level of throughput with a very small buffer, i.e. the Work En Route to the bottleneck is minimal, which obviously reduces the WIP. However, as mentioned before, a small change in the trigger level can reduce the throughput significantly. Since only a very small buffer is allowed in front of the bottleneck, and all bottleneck jobs are processed very quickly, a decrease in the trigger level can cause the bottleneck to starve readily.

Note that the SPTT dispatch rule has the same effect as in the flowshop. Many jobs can be processed faster, but at the expense of the jobs with longer operation times. When the shop is balanced, the combination of BNPR with the SPTT rule once again increases the WIP relative to the use of SPTT alone. However, when there is a bottleneck, the combination of the two results in the smallest ratio of WIP over throughput when the bottleneck is severe.

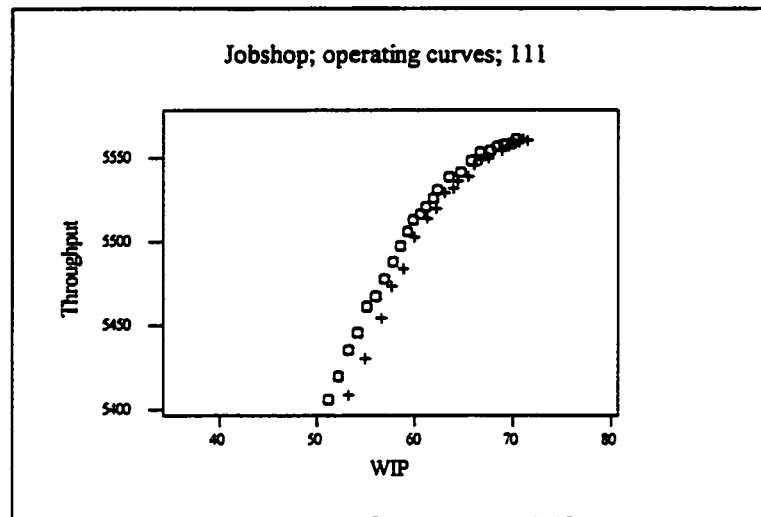


Figure 11: Operating curve for a balanced jobshop with no BNPR and FCFS

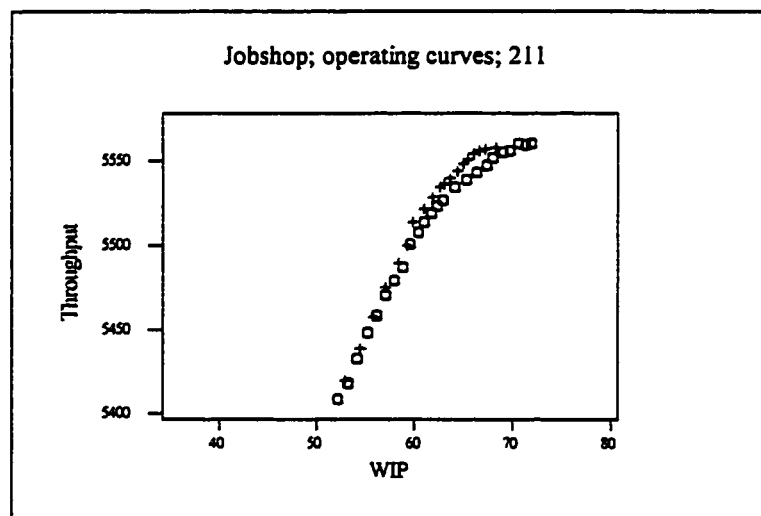


Figure 12: Operating curve for a jobshop with a light b/n, no BNPR and FCFS

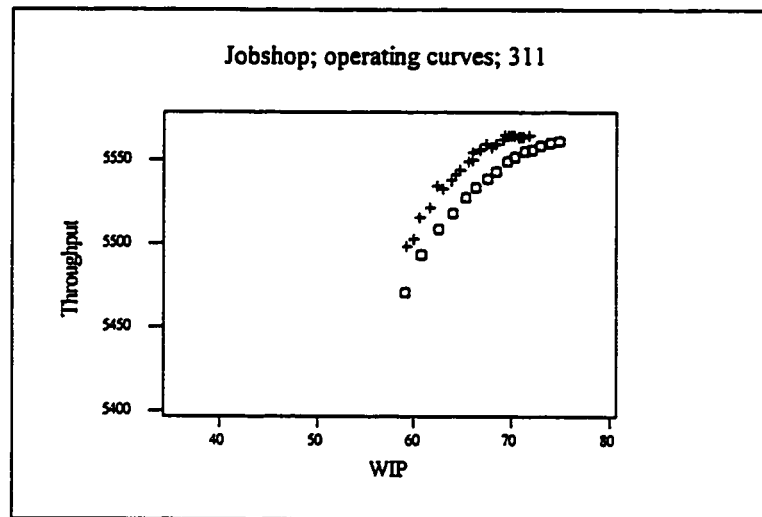


Figure 13: Operating curve for a jobshop with a severe b/n, no BNPR and FCFS

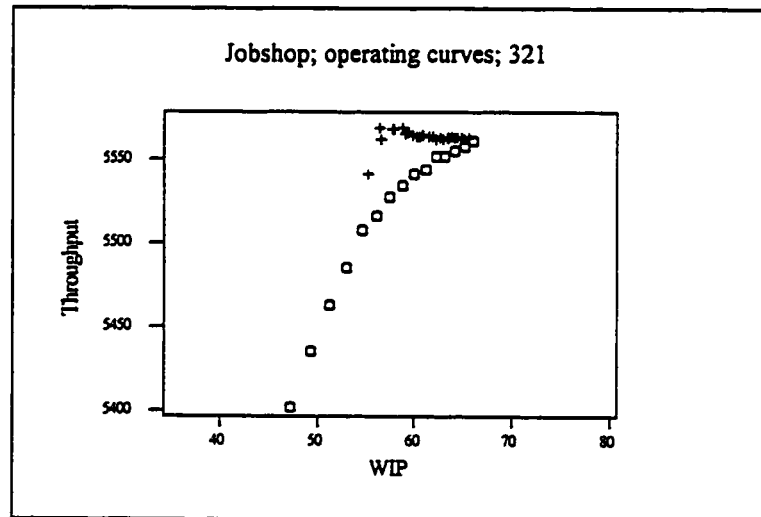


Figure 14: Operating curve for a jobshop with severe b/n, BNPR and FCFS

7.1.4.3 Comparison of the two shops

The flowshop and the jobshop are different in their flow patterns and therefore the same release control techniques will not necessary yield the same benefits under all scenarios. In the flowshop the flow is unidirectional, even though some jobs can bypass some machines, and the workload at each machine is relatively stable. *All* the jobs are delayed with the MH strategy when the shop is already overloaded and there are jobs in the release pool. Under these conditions, interarrival time variability affects the order pool queue length but not the variance of release time intervals. Therefore the external variation has no effect on the shop floor when this strategy is used. With the BIC strategy, on the contrary, one job out of six is a non-bottleneck job and is released as soon as it is created. When the shop is already heavily loaded, these jobs lengthen the queues even more, although not the bottleneck queue. Obviously this effect is smaller as the bottleneck becomes more severe, since in this situation the relative idle time for the non-bottleneck machines is higher. It is therefore more important to control all the external variations when the shop is nearly or completely balanced. As more unbalance appears, only the bottleneck jobs need to be controlled.

The behavior is different for the jobshop than for the flowshop. Since the routings are different from job to job, the length of the queues and the waiting times are less predictable. Restricting the aggregate WIP does not reduce the chance of congestion at a particular machine as much as for a flowshop. Since the new jobs are released on a First-Come-First-Served basis, these jobs may sometimes lengthen an already long queue instead of providing work for a machine at or near starvation. The MH strategy as

proposed is ineffective in reducing the variation introduced by unpredictable new job routings. The BIC strategy seems to be more robust regarding high variability in the routings. In this case it can make better use of the idle times on the non-bottleneck machines.

The results obtained with the operating curves are consistent with the ones of the queuing model. The flowtime is longer for the jobshop than for the flowshop. However, the results of the queuing model regarding each strategy are different from the ones obtained in this chapter. This is due to two reasons that were already mentioned in sections 4.3 and 4.6.4. First, the two strategies are modeled differently in the queuing model since shop arrivals are controlled rather than WIP levels. Second, the queuing model aggregates all the routings and estimates the flowtime of “average” jobs.

7.2. Trigger level selection

Since experimental results are to be compared using a particular point on each operating curve, the trigger levels need to be selected beforehand for each combination of settings. The operating curves are used to select the trigger levels.

Data was collected over 5000 hours in generating the operating curves. The arrival rate is equal to $1/0.9$. According to Little’s Law (Askin, Standridge, 1993) the throughput should be equal to $5000/0.9 = 5556$ jobs. Note that the purpose of the two strategies discussed in this thesis is to regulate the WIP in the shop while not lowering the

throughput. Therefore the trigger levels are chosen so that the WIP is at the minimum required to achieve the maximum level of throughput at every combination of settings. Furthermore, the assumption is made that, for both strategies, the WIP is the same under otherwise identical settings. In other words, the trigger levels are set so that for any combination of settings the WIP is equal to the maximum of the minimum WIP required, under MH or BIC, to obtain maximum throughput. This process is explained in Figure 15. Note that the WIP can vary from one combination of settings to another. Note as well that because of the way the experiments are set, the leadtime is the only measure that differentiates the two strategies.

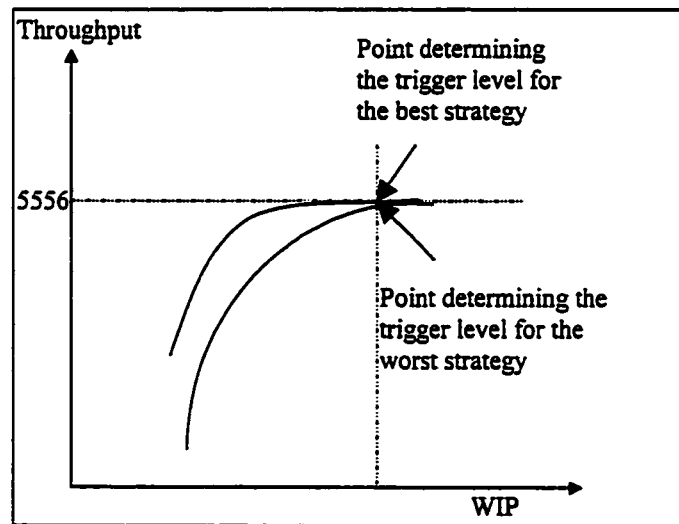


Figure 15: Scheme explaining the choice of the trigger levels

Table 12 lists the trigger levels chosen to be used in the generation of experimental results. These trigger levels are given in hours. A star is added to show

which strategy performs best under a particular setting. A star in parentheses indicates a small difference in the effectiveness of the two strategies.

Combination of settings ¹	Flowshop		Jobshop	
	MH strategy	BIC strategy	MH strategy	BIC strategy
111	57 *	10	79 *	11.5 (*)
112	41 *	6.75	64 *	8.75 (*)
121	50 *	5.5	65 *	3.5 *
122	41 *	4.5	66 *	3.5 *
211	50 *	11	75	12.5 *
212	43 *	8	62	10.25 *
221	47 *	6.25	67	6.25 *
222	41 *	5.5	59	5.25 *
311	54 *	12 (*)	79	15.5 *
312	43 *	6.25 (*)	66	13.25 *
321	49 *	9 (*)	69	9 *
322	41 *	7.5 (*)	61	7.75 *

Table 12: Trigger levels (in hours) chosen for the different settings for the ANOVA

¹ The first number of the column represents the level of the bottleneck, the second number the absence (1) or presence (2) of the priority rule, and the third number the dispatch rule used (FCFS=1, SPTT=2). For more information, see Table 10.

8. Analysis of Results

The operating curves, presented in the previous chapter, provide some insight into the relationship between the mean WIP and the throughput under various trigger levels. They are used to establish the proper trigger level for each combination of settings in the experimental plan. In this chapter, results using the selected trigger levels are presented and an analysis of variance (ANOVA) (Neter, Wassermann and Kutner, 1985) is carried out to compare statistically the effectiveness of the two order release strategies. The ANOVA computations are carried out on MINITAB, version 11.0 (Minitab Inc, 1985). First, the abbreviations used in the tables are explained. In section 8.2, the assumptions underlying the ANOVA are presented. Section 8.3 is devoted to the analysis of the throughput, the WIP and the leadtime responses. In section 8.4 the tardiness measures are discussed. In the last section, some conclusions are given.

For the sake of clarity, the factors and their levels are reported again in Table 13.

Factors	Levels
Release strategies (abbreviated RS)	1. MH 2. BIC
Level of the bottleneck (abbreviated B/N)	1. No bottleneck 2. Light bottleneck 3. Severe bottleneck
Bottleneck priority rule (abbreviated BNPR)	1. No BNPR 2. BNPR
Dispatch rule (abbreviated DR)	1. FCFS 2. SPTT

Table 13: Experimental factors

8.1. *Notation*

In the following tables, one standard format is used to illustrate the results obtained with Minitab. The first column refers to the effects and their interactions. The columns DF, SS, MS, F, P report the degree of freedom, the sum of squares, the mean squares, the value of the F-statistic and the P-value respectively. The symbol ‘*’ stands for the interaction between two factors. Note that the use of common random numbers allows the number of the replication to be added as an effect. In the summary tables, N represents the number of replication for each cell.

8.2. *Assumptions underlying the ANOVA*

The ANOVA procedure is based on several assumptions (Neter et al., 1985):

1. For each combination of settings, the errors, or residuals, are normally distributed.
2. The variance of the residuals is identical for each combination of settings.
3. For each combination of settings, the samples collected are random observations from the underlying probability distribution. These observations are independent.

Before analyzing the results, it is important to know these assumptions are not being violated. A normal probability plot (DeVor, Chang and Sutherland, 1992), in

conjunction with a Kolmogorov-Smirnov test, is a useful tool to check for the normality of the error terms. If the data is normally distributed the points of the plot should all fall in a straight line. The second assumption is often assessed by applying Bartlett's test (Walpole and Myers, 1989). A close look at the graphs plotting the residuals against the fitted values enables the third assumption to be checked. Unless otherwise specified, the confidence levels are set to 0.05.

These assumptions are checked for the flowshop model first. The jobshop model is examined next. The errors of the tardiness measures follow similar patterns as the ones for the actual leadtime. Therefore all the comments made for the leadtime in the following discussion are valid for the tardiness measure as well.

8.2.1. The flowshop

Normality of the data. Normal probability plots have been drawn for error terms for each of the three responses (throughput, leadtime and WIP) at each combination of settings. An example of such a plot is given in Figure 16. The Kolmogorov-Smirnov test indicates that the assumption of normality is rejected for the leadtime with several combinations of settings. The same test shows that the throughput is generally normally distributed when the MH strategy is used. When the Bottleneck Input Control (BIC) strategy is used, the data is not normally distributed for a few combination of settings. The WIP errors are normally distributed, except when the MH strategy is used for a shop with a strong bottleneck. In this latter case, there is some skewness in the distribution.

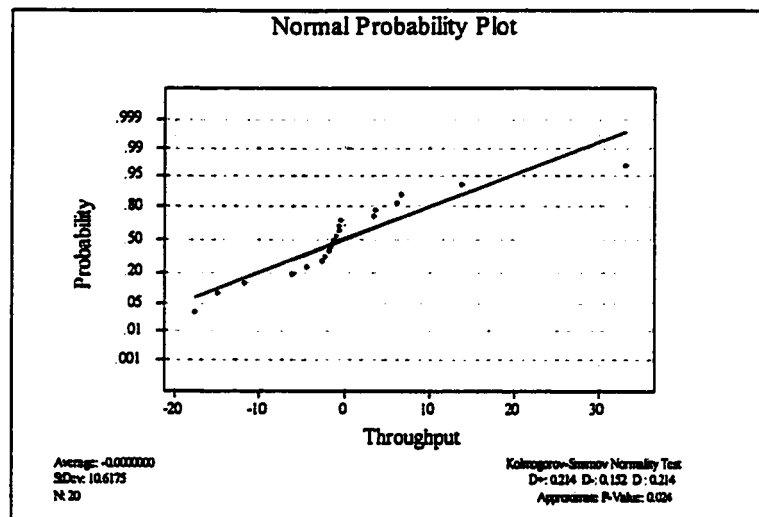


Figure 16: Example of a Normal Probability plot

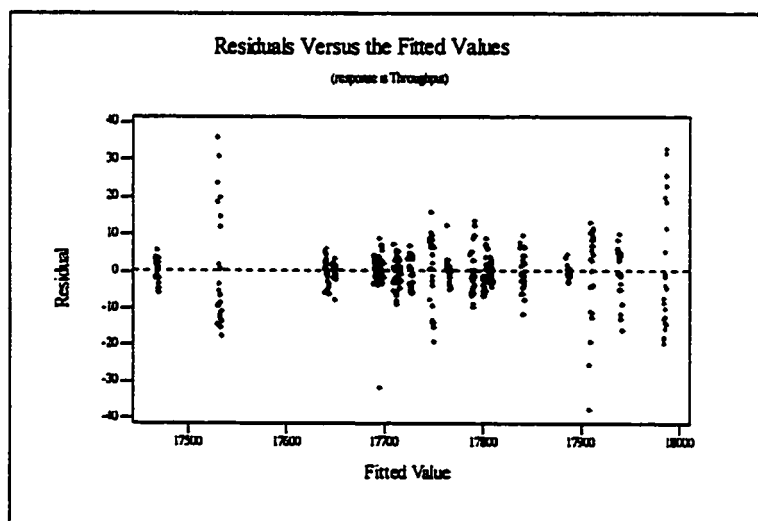


Figure 17: Residuals against fitted values for the throughput in the flowshop

Homogeneity of variance. Bartlett's test gives evidence that the variance is homogeneous for the throughput response over all the combinations of settings. However, the variances vary significantly from cell to cell for both the WIP and leadtime.

For these two measures Bartlett's test rejects the hypothesis of equal variances at a 0.01 confidence level.

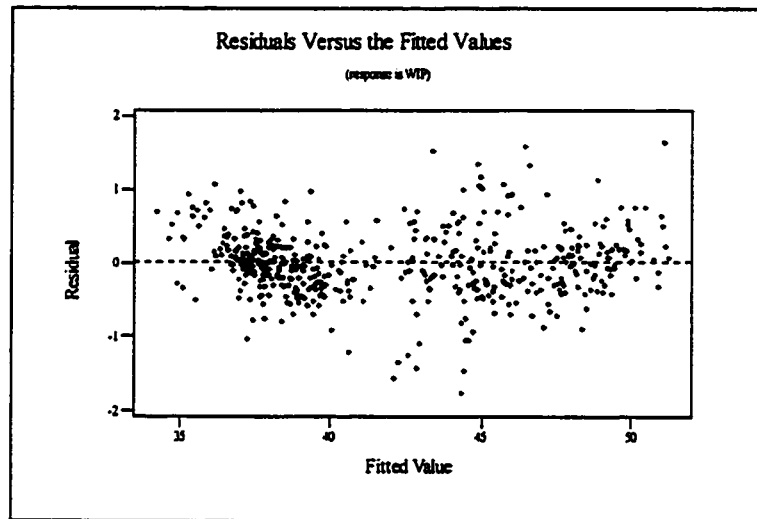


Figure 18: Residuals against fitted values for the WIP in the flowshop

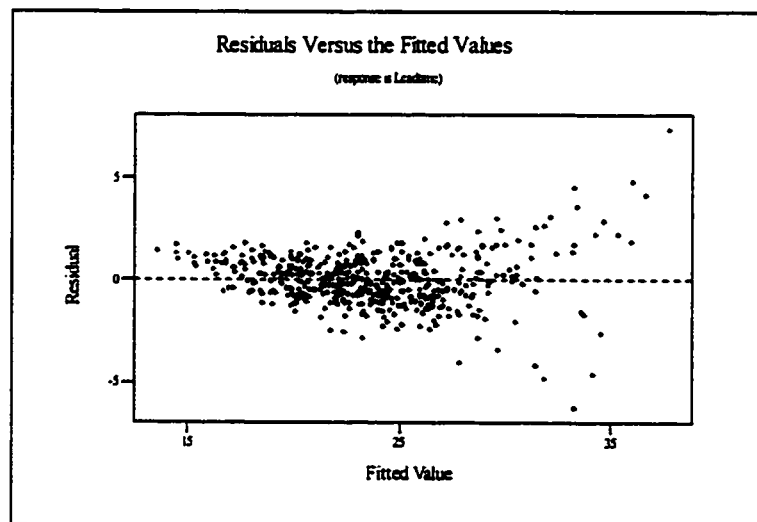


Figure 19: Residuals against fitted values for the leadtime in the flowshop

Randomness of residuals. Graphs of the residuals against the fitted values are given in Figure 17 for the throughput, in Figure 18 for the WIP and in Figure 19 for the leadtime. The use of common random numbers (see section 6.3.1) allows the number of the replication to be included as a factor in the ANOVA. By this means, some of the variation has been taken out and more accurate statistical results are obtained. As a consequence though, some residuals are relatively large because the leadtime measure is more sensitive to the input streams for some particular settings. This is true especially for the worst strategy. The residuals of the other two measures are randomly scattered.

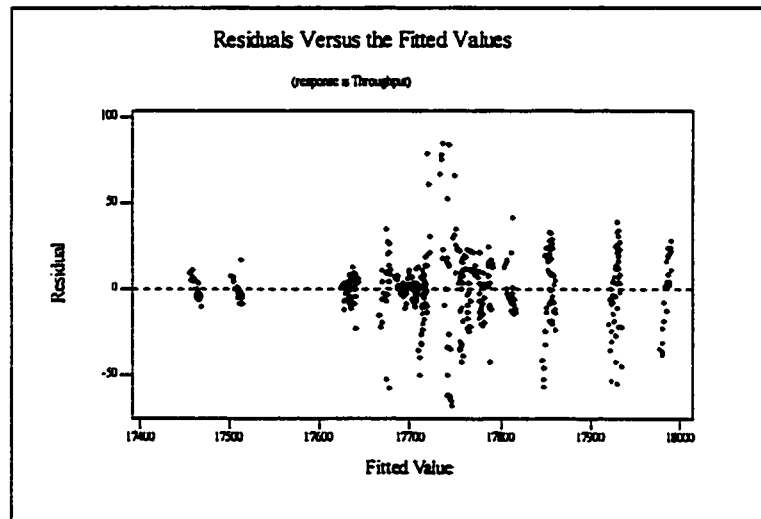


Figure 20: Residuals against fitted values for the throughput in the jobshop

8.2.2. The jobshop

Normality of the errors. The normal probability plots and the Kolmogorov-Smirnov tests indicate that the throughput is normally distributed, except for two combinations of settings. The WIP errors are normally distributed except in one case. The

data collected for the leadtime can be accepted as observations from a normal distribution when the MH strategy is used. On the contrary, for the BIC strategy, the hypothesis of normality is rejected most of the time for the leadtime. Skewness is present in the distribution of the data.

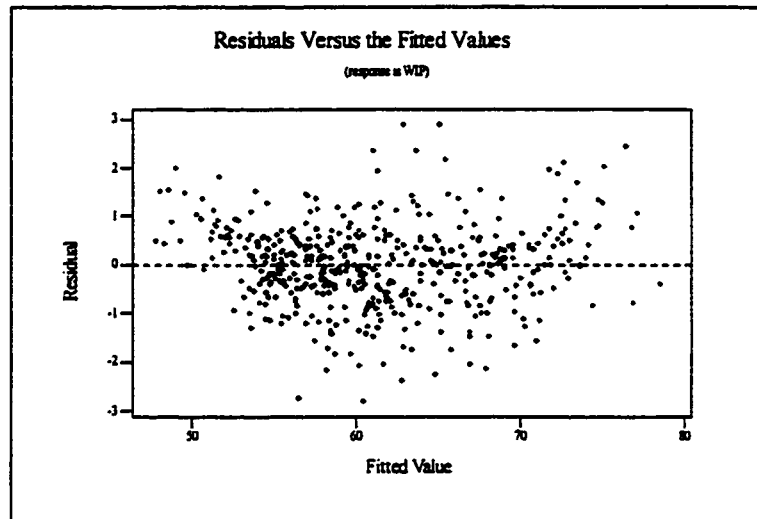


Figure 21: Residuals against fitted values for the WIP in the jobshop

Homogeneity of variance. As in the flowshop, the throughput variances are roughly the same for all combinations of settings. Using Bartlett's test, the hypothesis is accepted that the variances of the WIP are equal for all the cells of the ANOVA. The variances of the leadtime are not identical for all the combinations of settings.

Randomness of residuals. Graphs of the residuals against the fitted values are presented in Figure 20 for the throughput, in Figure 21 for the WIP, and in Figure 22 for the leadtime.

The errors can be considered random and fall within a reasonable range. A few large residuals can be observed for the throughput response. The residual is high for replication eleven (not shown) when the bottleneck is strong and the MH strategy is used, as well as for some other settings. As in the flowshop, the residuals for the leadtime seem to increase slightly for large leadtime observations. Again, the use of common random numbers allows for reduction in the variability. However, the leadtime measure is more sensitive to the input stream for some particular settings. Note that one observation has a large residual. This observation is again the eleventh replication of a particular combination of settings and corresponds to an observation with a large residual for the throughput.

8.2.3. Summary

Even though the assumptions of ANOVA are not completely satisfied, the ANOVA is judged to be an appropriate method of analysis. The most important assumption of ANOVA, that of independence between data in a sample, is maintained. Slight violations of other assumptions are often accepted, provided that the critical decisions are not based on P-values close to the level of significance chosen. The significance (or confidence) level is chosen to be 0.05. In fact, the F-test used in the ANOVA is robust against departures from normality, provided they are not of extreme form. The unequal error variances only slightly raise the significance of the F-test, since all the sample sizes are equal (Neter et al., 1985).

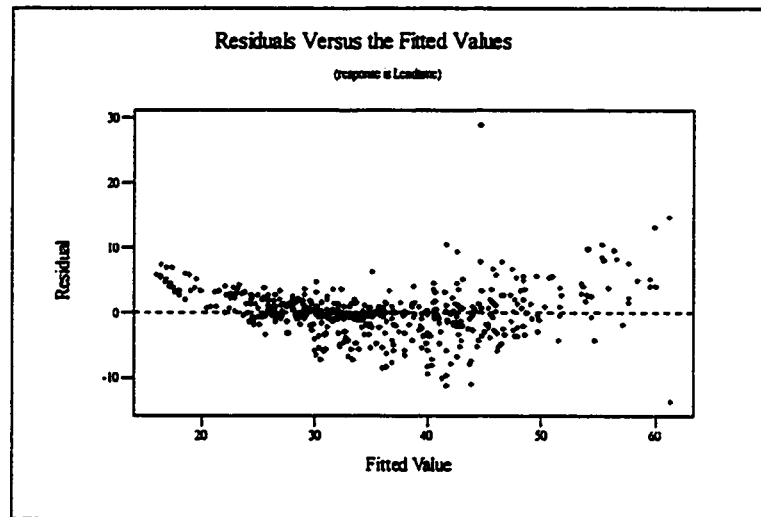


Figure 22: Residuals against fitted values for the leadtime in the jobshop

8.3. Results for the throughput, the WIP and the leadtime

The results for the flowshop are analyzed in section 8.3.1. The results for the jobshop are presented in section 8.3.2. The tardiness measures will be examined separately in section 8.4.

8.3.1. The flowshop

The experimental results for the flowshop are shown in Table 14. The presentation of the results is organized as follows. The throughput analysis is presented

first. The WIP response is examined next and finally the leadtime measure is analyzed. A summary of the results concludes the section.

RS	B/N	BNPR	DR	N	Throughput	WIP	Leadtime
MH	No	No	FCFS	20	17752	48.362	21.996
MH	No	No	SPTT	20	17751	36.905	18.397
MH	No	Yes	FCFS	20	17752	44.190	22.419
MH	No	Yes	SPTT	20	17752	37.606	20.195
MH	Li	No	FCFS	20	17751	45.898	25.277
MH	Li	No	SPTT	20	17750	38.541	19.291
MH	Li	Yes	FCFS	20	17751	43.233	24.268
MH	Li	Yes	SPTT	20	17751	37.978	21.076
MH	Sv	No	FCFS	20	17749	49.239	27.180
MH	Sv	No	SPTT	20	17750	39.678	22.390
MH	Sv	Yes	FCFS	20	17750	45.337	26.506
MH	Sv	Yes	SPTT	20	17750	38.812	23.990
BIC	No	No	FCFS	20	17751	48.151	24.154
BIC	No	No	SPTT	20	17751	37.289	21.794
BIC	No	Yes	FCFS	20	17748	44.785	23.801
BIC	No	Yes	SPTT	20	17748	37.595	26.590
BIC	Li	No	FCFS	20	17751	48.096	25.908
BIC	Li	No	SPTT	20	17750	37.825	21.986
BIC	Li	Yes	FCFS	20	17748	43.313	24.684
BIC	Li	Yes	SPTT	20	17751	37.782	23.771
BIC	Sv	No	FCFS	20	17748	49.387	28.317
BIC	Sv	No	SPTT	20	17749	38.812	23.821
BIC	Sv	Yes	FCFS	20	17749	44.934	25.087
BIC	Sv	Yes	SPTT	20	17750	38.189	24.873

Table 14 : Results summary table for the flowshop

8.3.1.1 The throughput

The experiment has been designed so that the throughput is equal for all the combination of settings. The summary table above shows that the throughput is roughly the same for all the combinations of settings. The results of the ANOVA for the throughput are given in Table 15. This table confirms that none of the effects are significant at the 0.05 confidence level. The number of the replication, however, is shown to account for much of the variability observed in throughput.

Source	DF	SS	MS	F	P
NRep	19	7512285	395383	6765.19	0.000
RS	1	161	161	2.75	0.098
B/N	2	148	74	1.27	0.282
BNPR	1	0	0	0.01	0.933
DR	1	1	1	0.02	0.877
RS*B/N	2	74	37	0.63	0.531
RS*BNPR	1	47	47	0.80	0.371
RS*DR	1	18	18	0.31	0.575
B/N*BNPR	2	82	41	0.70	0.496
B/N*DR	2	12	6	0.11	0.900
BNPR*DR	1	17	17	0.29	0.591
RS*B/N*BNPR	2	74	37	0.63	0.531
RS*B/N*DR	2	8	4	0.07	0.933
RS*BNPR*DR	1	11	11	0.20	0.659
B/N*BNPR*DR	2	30	15	0.26	0.771
RS*B/N*BNPR*DR	2	33	17	0.29	0.752
Error	437	25540	58		
Total	479	7538544			

Table 15: ANOVA for the throughput in the flowshop

8.3.1.2 The WIP

Figure 23 and Figure 24 illustrate the differences in the WIP for all the combinations of settings. The WIP is approximately the same for both strategies under otherwise identical settings. This is consistent with the way in which the trigger levels for order release are set.

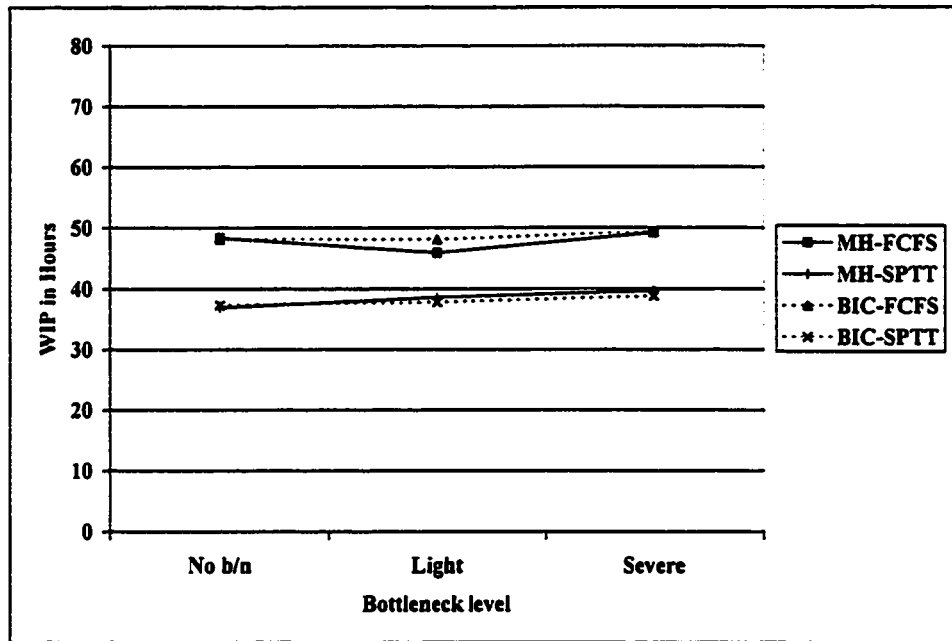


Figure 23: WIP in the flowshop without BNPR

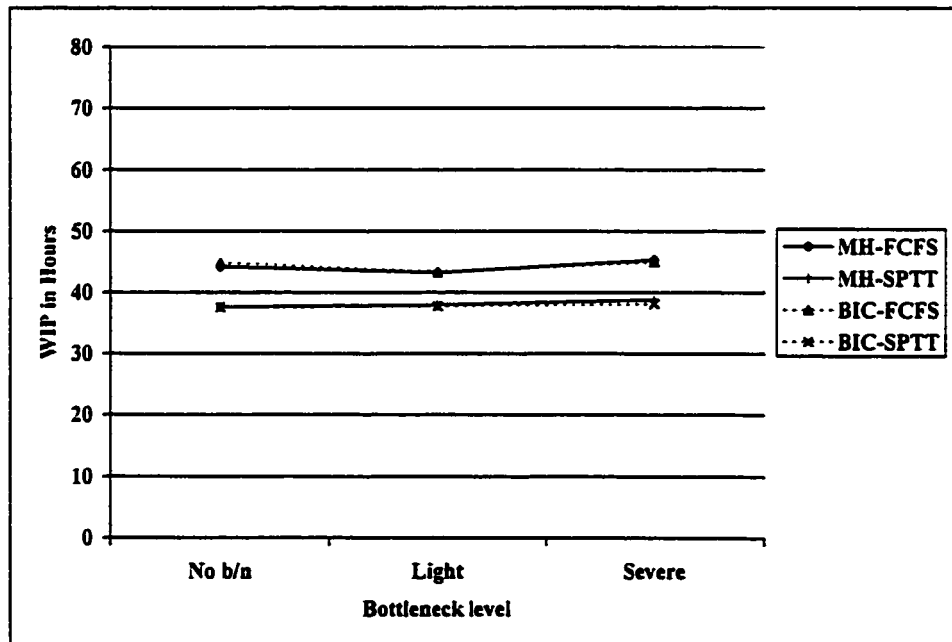


Figure 24: WIP in the flowshop with BNPR

The level of the bottleneck affects the level of WIP. Recall that the trigger level was chosen so that both strategies achieve the maximum throughput. When there is no bottleneck, BIC is a poor performer and almost the same level of WIP is necessary to achieve the maximum throughput as when a light bottleneck exists. As a matter of fact, when the shop is balanced, the bottleneck machine can process as many jobs as any other machine. Therefore over the same time period, more bottleneck jobs can be processed when the shop is balanced than when it is not. Moreover, the mean processing time of the non-bottleneck jobs is longer when the shop is balanced than when it is not. As a consequence, the non-bottleneck jobs are processed more slowly than when the shop is unbalanced and the shop is more heavily loaded at the non-bottleneck machines. Therefore, for the BIC strategy, there is no difference in the WIP between the shop without bottleneck and the one with a slight bottleneck. Otherwise, as the severity of the bottleneck increases, the WIP increases slightly.

The choice of the dispatch rule plays an important role on the WIP level. When SPTT is used instead of FCFS, it allows reducing the WIP by roughly 15 to 20 percent. This is consistent with previous findings. The bottleneck priority rule has a significant effect on the WIP level only when FCFS is used. In this case, its activation decreases the level of WIP. BNPR does not have much effect on the WIP when SPTT is used.

Table 16 contains the results of the ANOVA for the WIP response. It confirms that the level of WIP does not change with the release strategy, as expected. The most significant factors are the choice of the dispatch rule, as well as the choice of whether or not to implement BNPR. The ANOVA table indicates that the interaction of these two

factors is important as well. It shows that the level of the bottleneck affects the WIP, but to a lesser extent.

All the other interactions are significant at a 0.05 confidence level, but their effect on the WIP response is very small. The ANOVA results are therefore consistent with the above observations.

Source	DF	SS	MS	F	P
NRep	19	672.01	35.37	149.65	0.000
RS	1	0.12	0.12	0.51	0.477
B/N	2	193.84	96.92	410.09	0.000
BNPR	1	497.31	497.31	2104.24	0.000
DR	1	7988.31	7988.31	3.4E+04	0.000
RS*B/N	2	13.58	6.79	28.74	0.000
RS*BNPR	1	1.87	1.87	7.89	0.005
RS*DR	1	16.39	16.39	69.35	0.000
B/N*BNPR	2	13.75	6.87	29.09	0.000
B/N*DR	2	75.94	37.97	160.66	0.000
BNPR*DR	1	412.66	412.66	1746.07	0.000
RS*B/N*BNPR	2	5.18	2.59	10.96	0.000
RS*B/N*DR	2	12.85	6.43	27.19	0.000
RS*BNPR*DR	1	4.14	4.14	17.50	0.000
B/N*BNPR*DR	2	4.77	2.38	10.08	0.000
RS*B/N*BNPR*DR	2	18.46	9.23	39.05	0.000
Error	437	103.28	0.24		
Total	479	10034.47			

Table 16: ANOVA for the WIP in the flowshop

8.3.1.3 The leadtime

The leadtime measures are represented graphically in Figure 25 and Figure 26. The bottleneck level has an impact on the leadtime. Roughly, the stronger the bottleneck is the longer the leadtime gets. However, the graphs show evidence of interactions between the release strategy, the bottleneck level, the activation or not of the bottleneck priority rule and the dispatch rule.

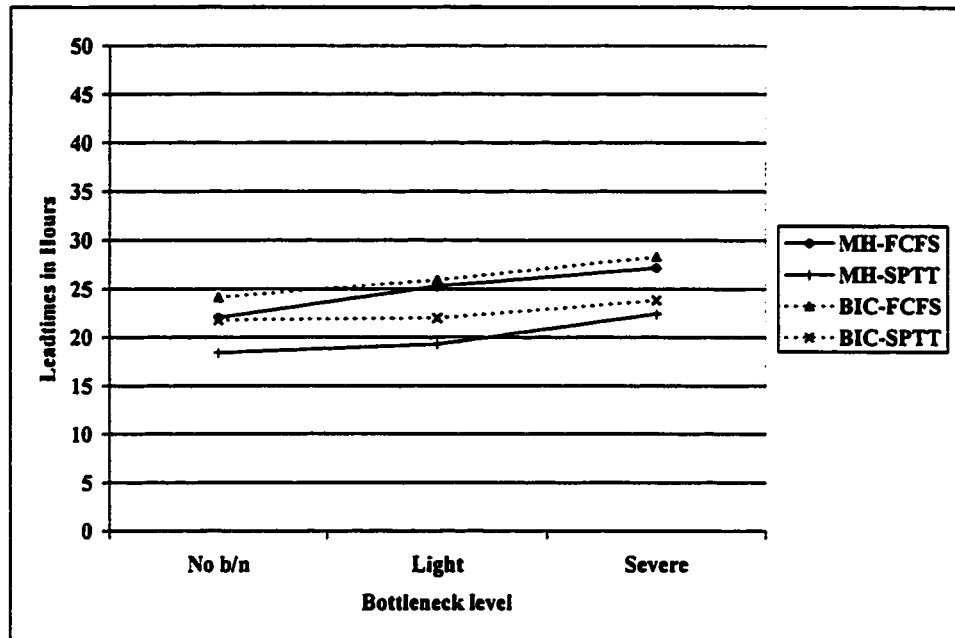


Figure 25: Leadtimes in the flowshop without BNPR

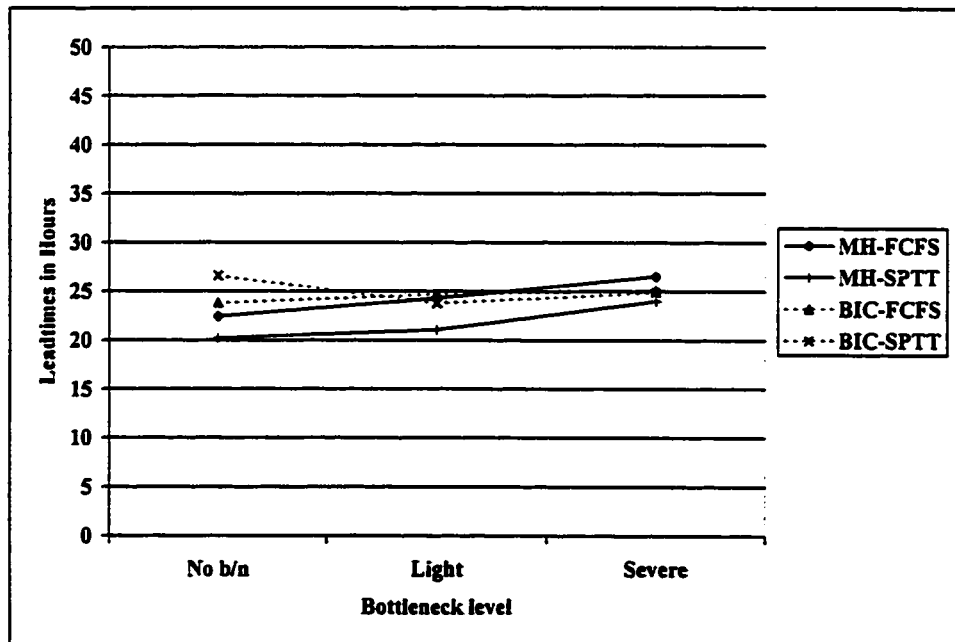


Figure 26: Leadtimes in the flowshop with BNPR

Without BNPR, the results are relatively straightforward (see Figure 25). The leadtime is shorter when the MH strategy is used rather than the BIC strategy. As for the WIP response, the use of SPTT results in a shorter leadtime. Although the graph shows some interactions, they seem to be relatively minor.

With BNPR, the two strategies do not behave similarly, although MH is on average better than BIC. It is important to identify how the two release strategies are affected by BNPR. The MH strategy controls the total workload. The bottleneck and non-bottleneck jobs are then released in the same order they are created. On the one hand, the bottleneck jobs do not have priority to be released before the non-bottleneck jobs. On the other hand, with the priority rule, the bottleneck jobs have processing priority. If too many bottleneck jobs are processed relative to non-bottleneck jobs, the shop load will consist of a disproportionate number of non-bottleneck jobs. Before any new bottleneck jobs can be released, some non-bottleneck jobs have to be processed to lower the total shop load.

The BIC strategy controls only the bottleneck jobs. With the priority rule, the bottleneck jobs are always given priority over the non-bottleneck jobs, independent of the proportion of non-bottleneck jobs in the shop. Therefore, as long as bottleneck jobs exist in the shop or in the order release pool, bottleneck jobs are processed and released while non-bottleneck jobs might wait longer in queue. In conclusion, BNPR will have less impact (negative or positive) on the MH strategy than on the BIC strategy.

Two factors are important in determining the effectiveness of BNPR: the dispatch rule and the level of the bottleneck. The dispatch rule certainly influences the effects of

BNPR. If a dispatch rule A already results in smaller average flowtimes than rule B, the introduction of BNPR will not impact both rules equally. Jobs will be released earlier on average with rule A. This is advantageous. However, if BNPR results in excessive priority for bottleneck jobs, non-bottleneck jobs will progress less quickly through the shop. In other words, BNPR may not improve the allocation of work in the shop as much for rule A as for rule B. It might even decrease the performance of the dispatch rule.

The level of the bottleneck plays an important role in determining the effectiveness of BNPR. When a shop is balanced, the bottleneck machine can process as many jobs as the non-bottleneck machines. As a result, there is no relative excess capacity left on the non-bottleneck machines to process the non-bottleneck jobs. On the contrary, when the shop is unbalanced, the bottleneck machine cannot process as many jobs as the non-bottleneck machines, and less bottleneck jobs are required in the system to keep the bottleneck machine busy. Therefore the non-bottleneck machines have some extra time (compared to the bottleneck machine) to process non-bottleneck jobs. Moreover, the mean processing times of the non-bottleneck jobs are shorter. The effectiveness of the bottleneck priority rule depends naturally on this amount of extra time relative to the dispatch rule chosen. If the dispatch rule is very effective in processing the jobs quickly through the shop, this extra time must be high. When this extra time exists, BNPR becomes effective.

The comments made above are based on observations from the graphs and results tables. As suggested above, it can be observed that the BIC strategy is affected more than the MH strategy by the bottleneck priority rule. The effectiveness of BNPR depends on

the dispatch rule chosen. In this flowshop, BNPR should not be used with SPTT, since in this case the bottleneck jobs have “too much” priority over the non-bottleneck jobs and this has a negative impact on the leadtime. This negative impact decreases, as the bottleneck becomes more important in the shop. The use of BNPR with FCFS is desirable if a bottleneck exists in the shop. In this case, the BIC strategy is improved more with BNPR than the MH strategy. As a matter of fact, with FCFS and BNPR, when the bottleneck becomes severe, the BIC strategy is more effective than the MH strategy.

The results of the ANOVA for the leadtime are presented in Table 17. The most significant effects are the dispatch rule, the release strategy and the bottleneck level. As observed in the graphs, the MH strategy performs better than the BIC strategy, and SPTT allows a reduction in the leadtime. The interaction between the release strategy and the dispatch rule is also significant. The ANOVA analysis confirms that the mean leadtime increases when the mean processing time of the bottleneck increases. As well, it indicates a strong interaction between the dispatch rule and BNPR. As explained above, the potential of BNPR is influenced by the dispatch rule. This interaction is stronger than the one between BNPR and the level of the bottleneck. Higher level interactions exist between BNPR and other factors. The most noticeable is the interaction between BNPR, the release strategy and the dispatch rule.

The interaction between the release strategy and the level of the bottleneck is relatively important and indicates that the differences in the leadtime between the two strategies becomes smaller as the mean processing time of the bottleneck machine

increases. The BIC strategy becomes more effective relatively to the MH strategy when a bottleneck exists in the shop.

Source	DF	SS	MS	F	P
NRrep	19	5572.68	293.30	158.52	0.000
RS	1	396.07	396.07	214.06	0.000
B/N	2	684.46	342.23	184.96	0.000
BNPR	1	37.99	37.99	20.53	0.000
DR	1	822.94	822.94	444.76	0.000
RS*B/N	2	162.21	81.10	43.83	0.000
RS*BNPR	1	1.00	1.00	0.54	0.462
RS*DR	1	145.00	145.00	78.37	0.000
B/N*BNPR	2	81.47	40.74	22.02	0.000
B/N*DR	2	101.80	50.90	27.51	0.000
BNPR*DR	1	297.23	297.23	160.64	0.000
RS*B/N*BNPR	2	35.54	17.77	9.60	0.000
RS*B/N*DR	2	16.70	8.35	4.51	0.011
RS*BNPR*DR	1	29.98	29.98	16.20	0.000
B/N*BNPR*DR	2	0.91	0.45	0.25	0.782
RS*B/N*BNPR*DR	2	15.84	7.92	4.28	0.014
Error	437	808.58	1.85		
Total	479	9210.40			

Table 17: ANOVA for the leadtime in the flowshop

8.3.1.4 Summary

The MH strategy performs better with respect to the leadtime when the shop is balanced, or when a slight bottleneck is present ('B/N'=2). When the bottleneck is severe and SPTT is used, the MH strategy remains slightly superior. However, when BNPR is used with FCFS, the BIC strategy performs slightly better than the MH strategy. SPTT is effective in maintaining a low WIP along with a short leadtime.

The effectiveness of BNPR in the flowshop is conditioned by three factors. The most important one is the dispatch rule chosen. BNPR is not effective when SPTT is

used. BNPR has more effect if the BIC strategy is used instead of the MH strategy. To a lesser extent, the level of the bottleneck changes the effects of BNPR. In particular, BNPR should not be used in a balanced shop.

8.3.2. The jobshop

The experimental results for the jobshop are given in Table 18. The results for the jobshop are presented in the same fashion as for the flowshop. The throughput response is examined first. The WIP measure is then taken into consideration and finally the leadtime is included. A summary of the results concludes the section.

8.3.2.1 *The throughput*

The experiment was designed so that the throughput should be equal for all the combinations of settings. The result summary table (see Table 18) indicates that there is little variation in the mean throughput levels. The ANOVA output generated for the throughput is given in Table 19. As for the flowshop, none of the effects are significant at the 0.05 level, and therefore it can be considered that the throughput is identical for all combinations of settings.

s	B/N	BNPR	DR	N	Throughput	WIP	Leadtime
MH	No	No	FCFS	20	17751	68.589	32.893
MH	No	No	SPTT	20	17748	56.816	28.810
MH	No	Yes	FCFS	20	17747	59.795	36.168
MH	No	Yes	SPTT	20	17751	54.267	30.756
MH	Li	No	FCFS	20	17742	69.050	41.768
MH	Li	No	SPTT	20	17743	57.494	35.953
MH	Li	Yes	FCFS	20	17744	61.522	38.011
MH	Li	Yes	SPTT	20	17745	54.796	35.445
MH	Sv	No	FCFS	20	17741	73.131	47.659
MH	Sv	No	SPTT	20	17742	61.522	41.834
MH	Sv	Yes	FCFS	20	17739	64.297	44.053
MH	Sv	Yes	SPTT	20	17741	57.397	41.734
BIC	No	No	FCFS	20	17751	68.063	33.952
BIC	No	No	SPTT	20	17748	56.714	33.850
BIC	No	Yes	FCFS	20	17749	59.722	47.762
BIC	No	Yes	SPTT	20	17747	54.527	44.812
BIC	Li	No	FCFS	20	17747	67.108	37.380
BIC	Li	No	SPTT	20	17747	56.463	32.183
BIC	Li	Yes	FCFS	20	17750	60.878	28.161
BIC	Li	Yes	SPTT	20	17747	53.953	27.688
BIC	Sv	No	FCFS	20	17749	71.006	34.380
BIC	Sv	No	SPTT	20	17749	60.278	29.353
BIC	Sv	Yes	FCFS	20	17751	63.464	30.297
BIC	Sv	Yes	SPTT	20	17748	55.942	28.122

Table 18: Result summary table for the jobshop

Source	DF	SS	MS	F	P
NRep	19	7827119	411954	870.27	0.000
RS	1	1763	1763	3.73	0.054
B/N	2	1449	724	1.53	0.218
BNPR	1	0	0	0.00	0.990
DR	1	26	26	0.06	0.814
RS*B/N	2	1747	873	1.85	0.159
RS*BNPR	1	0	0	0.00	1.000
RS*DR	1	205	205	0.43	0.510
B/N*BNPR	2	152	76	0.16	0.852
B/N*DR	2	26	13	0.03	0.973
BNPR*DR	1	16	16	0.03	0.854
RS*B/N*BNPR	2	56	28	0.06	0.942
RS*B/N*DR	2	8	4	0.01	0.991
RS*BNPR*DR	1	170	170	0.36	0.549
B/N*BNPR*DR	2	119	60	0.13	0.882
RS*B/N*BNPR*DR	2	16	8	0.02	0.984
Error	437	206861	473		
Total	479	8039735			

Table 19: ANOVA for the throughput in the jobshop

8.3.2.2 *The WIP*

Figure 27 and Figure 28 illustrate the levels of WIP for all the combinations of settings. The order release trigger levels were set so that the WIP levels would be the same for both strategies. However, when a bottleneck exists in the shop, the graphs show that the WIP levels for the BIC strategy are slightly lower than the ones for the MH strategy.

The WIP level required to meet the throughput objectives goes up with the bottleneck level. The increase is particularly important when the bottleneck becomes severe. SPTT allows a substantial reduction in the WIP. As well, the activation of BNPR reduces the WIP level. However, this reduction is more important when FCFS is used rather than SPTT. Moreover, this reduction is bigger as the bottleneck becomes more severe.

Table 20 contains the results of the ANOVA for the WIP measure. It confirms that the WIP is not identical for both strategies under otherwise identical settings. In addition, there exists some interaction between the release strategy and the bottleneck level.

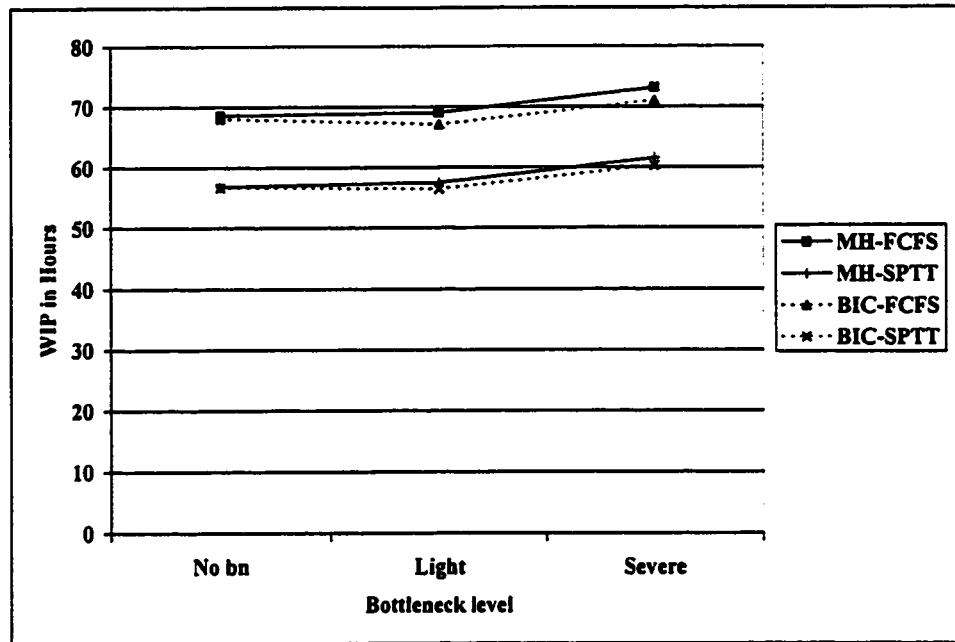


Figure 27: WIP in the jobshop without BNPR

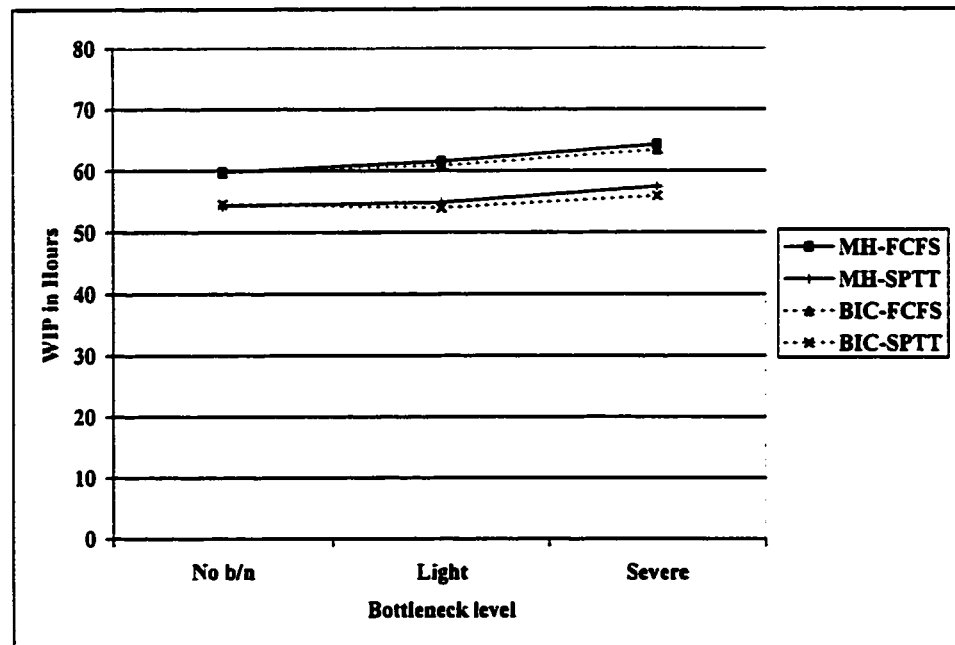


Figure 28: WIP in the jobshop with BNPR

Source	DF	SS	MS	F	P
NRep	19	3988.85	209.94	264.44	0.000
RS	1	92.89	92.89	117.01	0.000
B/N	2	1238.73	619.37	780.14	0.000
BNPR	1	3593.90	3593.90	4526.83	0.000
DR	1	9443.89	9443.89	1.2E+04	0.000
RS*B/N	2	37.34	18.67	23.52	0.000
RS*BNPR	1	9.53	9.53	12.01	0.001
RS*DR	1	2.49	2.49	3.13	0.077
B/N*BNPR	2	43.07	21.53	27.12	0.000
B/N*DR	2	11.11	5.55	7.00	0.001
BNPR*DR	1	694.23	694.23	874.44	0.000
RS*B/N*BNPR	2	0.57	0.28	0.36	0.699
RS*B/N*DR	2	0.38	0.19	0.24	0.789
RS*BNPR*DR	1	6.07	6.07	7.65	0.006
B/N*BNPR*DR	2	29.39	14.70	18.51	0.000
RS*B/N*BNPR*DR	2	2.66	1.33	1.67	0.189
Error	437	346.94	0.79		
Total	479	19542.04			

Table 20: ANOVA for the WIP in the jobshop

The ANOVA table confirms that the dispatch rule, the bottleneck priority rule and the bottleneck level are the most important effects on the WIP level. The interaction between the dispatch rule and BNPR has to be considered as well. Although other interactions are significant, their effect on the WIP level is minimal.

8.3.2.3 The leadtime

The leadtime measures are presented graphically in Figure 29 and Figure 30. A first look at the graphs shows that the BIC strategy becomes more effective as a bottleneck is introduced. At the same time, the effectiveness of the MH strategy decreases. SPTT, used with or without BNPR, reduces the leadtime. However, the proportion of the reduction is not always the same and depends mainly on the release strategy and on the bottleneck priority rule.

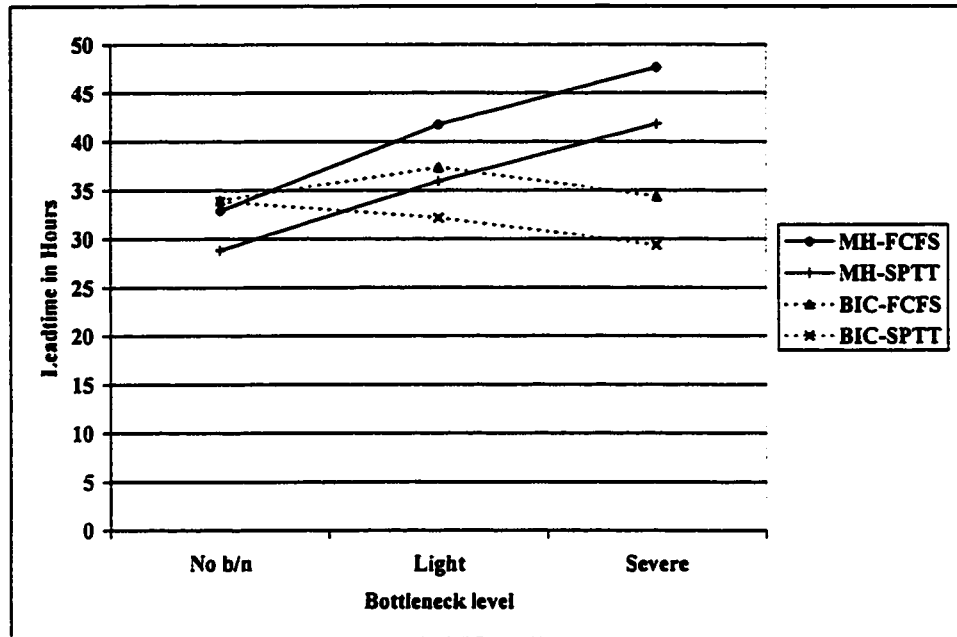


Figure 29: Leadtime in the jobshop without BNPR

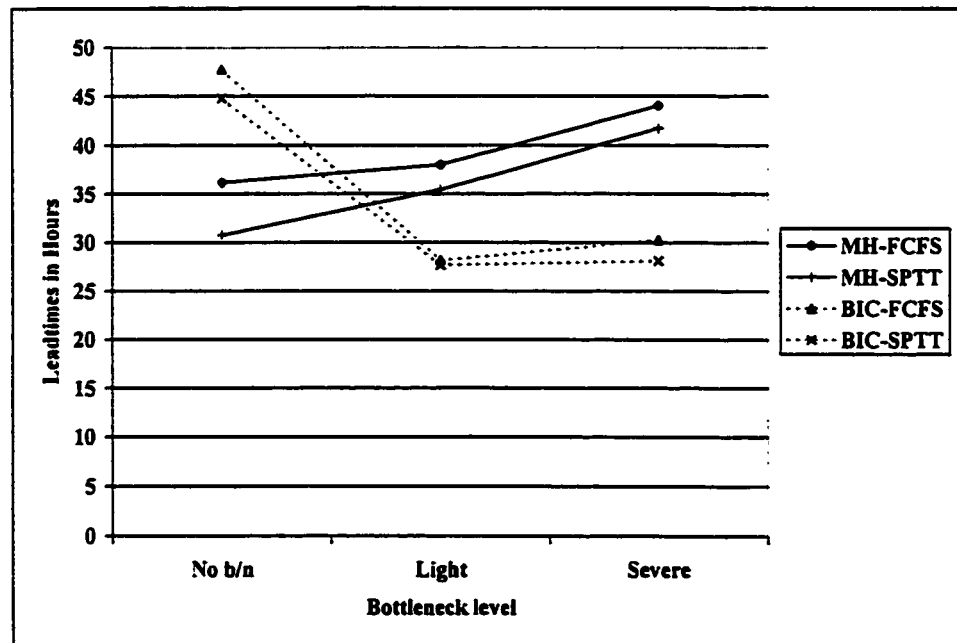


Figure 30: Leadtime in the jobshop with BNPR

The results with and without BNPR are relatively different. When the shop is balanced, BNPR should not be used, as far as the leadtime measure is concerned. As a matter of fact, when the shop is balanced, the leadtime increases for both strategies with BNPR. The “negative” effect of BNPR is particularly important for the BIC strategy. When the shop is balanced, the bottleneck machine can process as many jobs as the non-bottleneck machines. Therefore the non-bottleneck machines have little time left to process non-bottleneck jobs. When BNPR is activated, the bottleneck jobs are processed more quickly, but at the expense of the non-bottleneck jobs. As was explained for the flowshop, the BIC strategy will release bottleneck jobs independently of the number of non-bottleneck jobs in the shop. As a consequence, the bottleneck jobs are processed very quickly, and the non-bottleneck jobs wait in queues longer on average. On the contrary, the MH strategy takes into account both the bottleneck and non-bottleneck jobs when deciding on a new release. Therefore, the use of BNPR affects the BIC strategy more than the MH strategy. The graphs confirm this behavior.

When a bottleneck exists in the shop, BNPR allows a reduction in the leadtimes, since the non-bottleneck machines have then enough excess capacity to process non-bottleneck jobs in a reasonable time. The size of the reduction varies essentially with the release strategy and the dispatch rule chosen. The reduction is more substantial when FCFS is used instead of SPTT, and when the BIC strategy is used instead of the MH strategy.

The results of the ANOVA for the leadtime are presented in Table 21. It shows that the release strategy and the dispatch rule influence the leadtime the most. The

interaction between the release strategy and the bottleneck level is very important. It confirms that the choice of the release strategy depends on the bottleneck level. Finally, the ANOVA shows that the effect of BNPR on the leadtime depends on the bottleneck level and to a lesser extent, on its interaction with the release strategy. In Table 22, the mean leadtimes in the jobshop are given after they have been aggregated over the two dispatch rules.

8.3.2.4 Summary

The MH strategy is better than the BIC strategy when the shop is balanced. As soon as a bottleneck exists in the shop, the BIC strategy performs better. The leadtime is shorter when SPTT is used rather than FCFS. BNPR reduces both the WIP and the leadtime when a bottleneck exists in the shop, be it used with FCFS or SPTT.

Source	DF	SS	MS	F	P
NRep	19	25681.9	1351.7	84.01	0.000
RS	1	1852.1	1852.1	115.12	0.000
B/N	2	549.6	274.8	17.08	0.000
BNPR	1	7.5	7.5	0.46	0.496
DR	1	1466.1	1466.1	91.13	0.000
RS*B/N	2	9383.9	4691.9	291.63	0.000
RS*BNPR	1	60.1	60.1	3.74	0.054
RS*DR	1	84.9	84.9	5.28	0.022
B/N*BNPR	2	3252.8	1626.4	101.09	0.000
B/N*DR	2	9.8	4.9	0.30	0.737
BNPR*DR	1	85.9	85.9	5.34	0.021
RS*B/N*BNPR	2	1125.1	562.5	34.96	0.000
RS*B/N*DR	2	39.4	19.7	1.23	0.295
RS*BNPR*DR	1	0.4	0.4	0.03	0.873
B/N*BNPR*DR	2	217.7	108.8	6.77	0.001
RS*B/N*BNPR*DR	2	11.9	5.9	0.37	0.692
Error	437	7030.8	16.1		
Total	479	50859.8			

Table 21: ANOVA for the leadtime in the jobshop

RS	B/N	BNPR	N	Throughput	WIP	Leadtime
MH	No	No	40	17750	62.703	30.852
MH	No	Yes	40	17749	57.031	33.462
MH	Li	No	40	17742	63.272	38.861
MH	Li	Yes	40	17745	58.159	36.728
MH	Sv	No	40	17742	67.326	44.746
MH	Sv	Yes	40	17740	60.847	42.894
BIC	No	No	40	17749	62.389	33.902
BIC	No	Yes	40	17748	57.125	46.287
BIC	Li	No	40	17747	61.786	34.782
BIC	Li	Yes	40	17748	57.416	27.925
BIC	Sv	No	40	17749	65.641	31.867
BIC	Sv	Yes	40	17749	59.703	29.210

Table 22: Results aggregated over the dispatch rules for the jobshop

8.4. *Tardiness measures*

It is also important to compare the performance based on tardiness measures. They reflect the leadtime of the slowest jobs in the shop. It is important to know how many jobs are completed after their due date and how tardy these jobs are. For this purpose two different tardiness measures are computed. The tardiness (T) is set to zero if the job is completed before its due date. Otherwise T is equal to the difference between the completion time and the due date. The percentage of tardy jobs (TD) measures the proportion of jobs completed after their due date.

Two due dates setting rules have been used in this study, namely the PPW (processing plus waiting time) and the TWK (total work content) rules. A definition of these notions is given in section 3.1. Recall that three different k tightness values have been tested: 8.368, 10.474 and 12.579 for the TWK rule and 7, 9 and 11 for the PPW rule. This results in average planned leadtimes of 39.5, 49.5 and 59.5. Therefore six

tardiness measures are defined. MT1, MT2 and MT3 are the three TWK tardiness measures, when $k = 8.368$, 10.474 and 12.579 respectively. Similarly, the notation MT4, MT5 and MT6 refer to the PPW tardiness measures. Following the same pattern, the percentage of tardy jobs is numbered TD1 to TD6.

The results for the flowshop are presented in the next section. Section 8.4.2 focuses on the results for the jobshop.

8.4.1. The flowshop

The mean tardiness measures are presented in Table 23. In Table 24, the percentages of tardy jobs are given. In Figure 31 and Figure 32 the mean tardiness measures are represented graphically. The percentage of tardy jobs is illustrated in Figure 33 and Figure 34. Note that some lines on the graphs are overlapped. Since all the results for the different tardiness measures are very comparable, the graphs show the tardiness measures only when the due dates are tight.

					Mean tardiness					
					TWK			PPW		
					<i>Tight</i>	<i>Medium</i>	<i>Loose</i>	<i>Tight</i>	<i>Medium</i>	<i>Loose</i>
RS	B/N	BNPR	DR	N	MT1	MT2	MT3	MT4	MT5	MT6
MH	No	No	FCFS	20	1.0540	0.4735	0.2185	0.7825	0.2945	0.1100
MH	No	No	SPTT	20	0.6415	0.2710	0.1175	0.6430	0.2515	0.0965
MH	No	Yes	FCFS	20	2.0555	1.1865	0.6925	1.7865	0.9460	0.4895
MH	No	Yes	SPTT	20	1.4425	0.7360	0.3755	1.3640	0.6410	0.2895
MH	Li	No	FCFS	20	2.2870	1.2365	0.6785	1.9345	0.9590	0.4720
MH	Li	No	SPTT	20	0.8410	0.3650	0.1580	0.8450	0.3385	0.1285
MH	Li	Yes	FCFS	20	2.3750	1.3260	0.7500	2.0260	1.0195	0.5015
MH	Li	Yes	SPTT	20	1.5710	0.8015	0.4075	1.4830	0.6935	0.3145
MH	Sv	No	FCFS	20	3.0685	1.7320	0.9960	2.6770	1.3930	0.7290
MH	Sv	No	SPTT	20	1.8510	0.9780	0.5275	1.8355	0.9235	0.4650
MH	Sv	Yes	FCFS	20	3.2095	1.8730	1.1105	2.8070	1.5110	0.8115
MH	Sv	Yes	SPTT	20	2.5890	1.4585	0.8335	2.4830	1.3210	0.7020
BIC	No	No	FCFS	20	2.1280	1.1505	0.6225	1.8360	0.9090	0.4200
BIC	No	No	SPTT	20	2.0135	1.1215	0.6155	1.9830	1.0515	0.5310
BIC	No	Yes	FCFS	20	2.4155	1.4245	0.8640	2.1250	1.1750	0.6615
BIC	No	Yes	SPTT	20	3.6455	2.1400	1.2660	3.4705	1.9430	1.0770
BIC	Li	No	FCFS	20	2.9740	1.7445	1.0300	2.6610	1.4760	0.7990
BIC	Li	No	SPTT	20	2.0230	1.1185	0.6135	2.0085	1.0620	0.5410
BIC	Li	Yes	FCFS	20	2.5590	1.4630	0.8495	2.2260	1.1740	0.6155
BIC	Li	Yes	SPTT	20	2.4335	1.3505	0.7610	2.2970	1.2115	0.6355
BIC	Sv	No	FCFS	20	4.2070	2.6365	1.6805	3.8620	2.3160	1.3985
BIC	Sv	No	SPTT	20	2.8125	1.6575	0.9820	2.8060	1.5970	0.9055
BIC	Sv	Yes	FCFS	20	2.6945	1.5565	0.9155	2.3540	1.2570	0.6720
BIC	Sv	Yes	SPTT	20	2.8520	1.6150	0.9310	2.7155	1.4695	0.7940

Table 23: Results summary table for MT in the flowshop

					Percentage of tardy jobs					
					TWK			PPW		
					<i>Tight</i>	<i>Medium</i>	<i>Loose</i>	<i>Tight</i>	<i>Medium</i>	<i>Loose</i>
RS	B/N	BNPR	DR	N	TD1	TD2	TD3	TD4	TD5	TD6
MH	No	No	FCFS	20	10.685	4.864	2.3095	8.102	3.135	1.1960
MH	No	No	SPTT	20	6.497	2.839	1.2750	6.527	2.602	1.0545
MH	No	Yes	FCFS	20	14.142	8.345	5.0370	12.409	6.966	3.8005
MH	No	Yes	SPTT	20	11.560	6.265	3.3915	11.081	5.615	2.7395
MH	Li	No	FCFS	20	16.987	9.198	5.1735	14.284	7.166	3.6950
MH	Li	No	SPTT	20	8.045	3.702	1.7300	8.086	3.463	1.4200
MH	Li	Yes	FCFS	20	17.009	9.803	5.7310	14.908	7.948	4.1110
MH	Li	Yes	SPTT	20	12.526	6.759	3.6540	12.061	6.015	2.9190
MH	Sv	No	FCFS	20	20.615	11.790	6.8660	18.147	9.616	5.1115
MH	Sv	No	SPTT	20	13.344	7.166	3.9565	13.263	6.783	3.5005
MH	Sv	Yes	FCFS	20	20.764	12.400	7.4715	18.580	10.238	5.6875
MH	Sv	Yes	SPTT	20	17.209	9.977	5.8250	16.678	9.130	4.9730
BIC	No	No	FCFS	20	14.841	8.300	4.7430	12.635	6.801	3.5840
BIC	No	No	SPTT	20	12.598	7.341	4.3935	12.422	7.046	3.9940
BIC	No	Yes	FCFS	20	15.775	9.187	5.5465	13.786	7.585	4.2260
BIC	No	Yes	SPTT	20	21.612	13.022	7.8450	20.708	11.886	6.7420
BIC	Li	No	FCFS	20	17.910	10.598	6.4920	15.771	8.984	5.2795
BIC	Li	No	SPTT	20	12.876	7.407	4.3670	12.817	7.123	3.9735
BIC	Li	Yes	FCFS	20	17.259	10.037	5.9370	15.128	8.227	4.4295
BIC	Li	Yes	SPTT	20	16.441	9.260	5.2785	15.540	8.197	4.3865
BIC	Sv	No	FCFS	20	21.986	13.665	8.7575	20.030	11.979	7.2240
BIC	Sv	No	SPTT	20	15.910	9.607	5.8455	15.955	9.249	5.4335
BIC	Sv	Yes	FCFS	20	17.829	10.415	6.2050	15.700	8.570	4.6385
BIC	Sv	Yes	SPTT	20	18.329	10.549	6.0925	17.512	9.519	5.1810

Table 24: Results summary table for TD in the flowshop

The percentage of tardy jobs varies roughly between 1 and 8 percent when the due dates are loose and between 6 to 21 percent when the due dates are tight. As expected, the tardiness measures follow the same patterns as those of the actual leadtime. In fact, when the actual leadtime is long, the tardiness measures are high as well. There is no evidence that the use of SPTT results in higher tardiness in this flowshop, except when the shop is balanced. In this case, for the PPW rule and the BIC strategy, SPTT results in higher tardiness than FCFS.

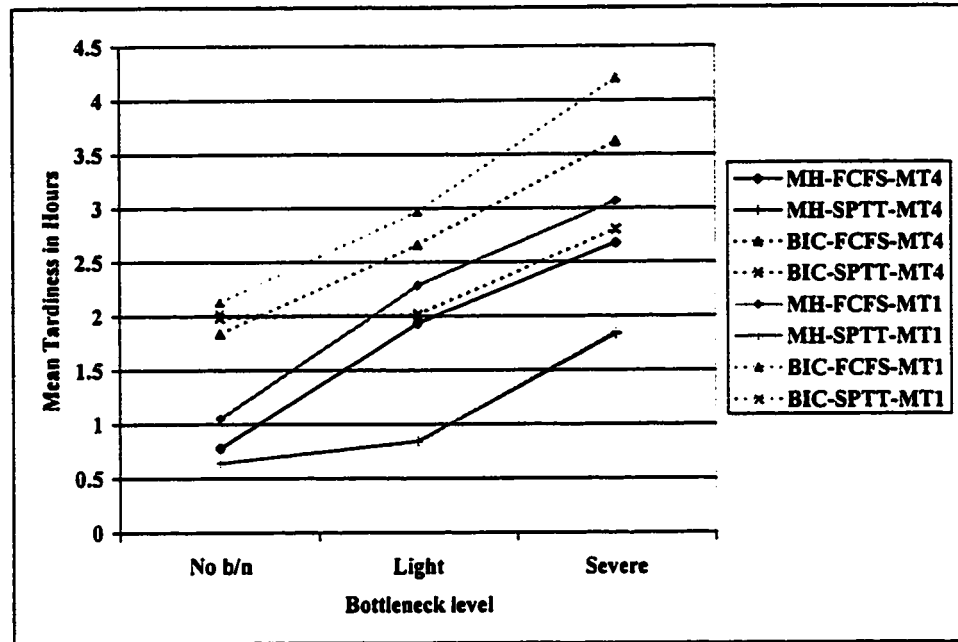


Figure 31: Mean tardiness (MT1, MT4) in the flowshop without BNPR

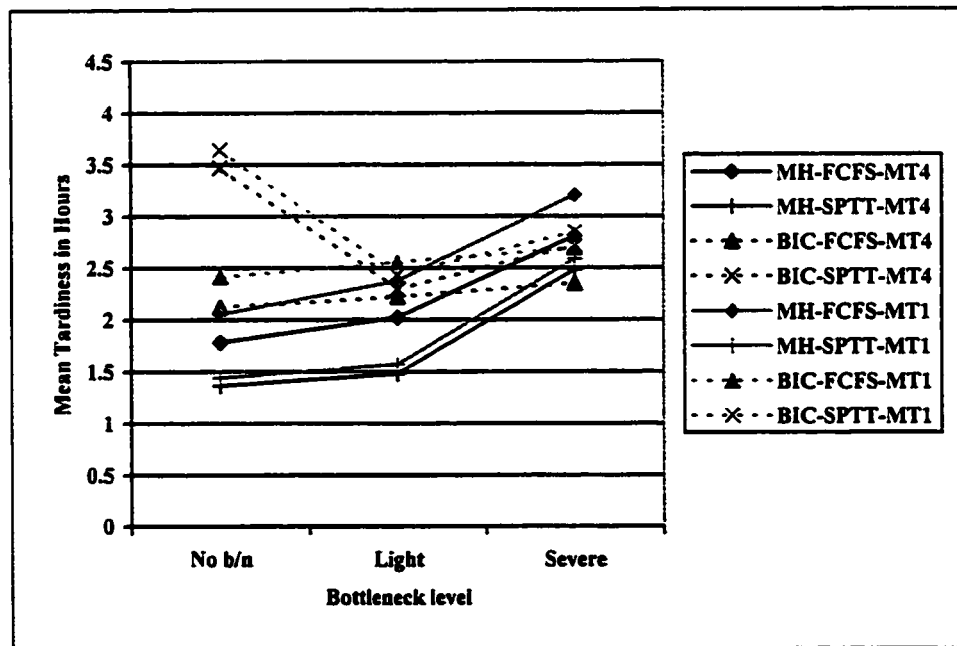


Figure 32: Mean tardiness (MT1, MT4) in the flowshop with BNPR

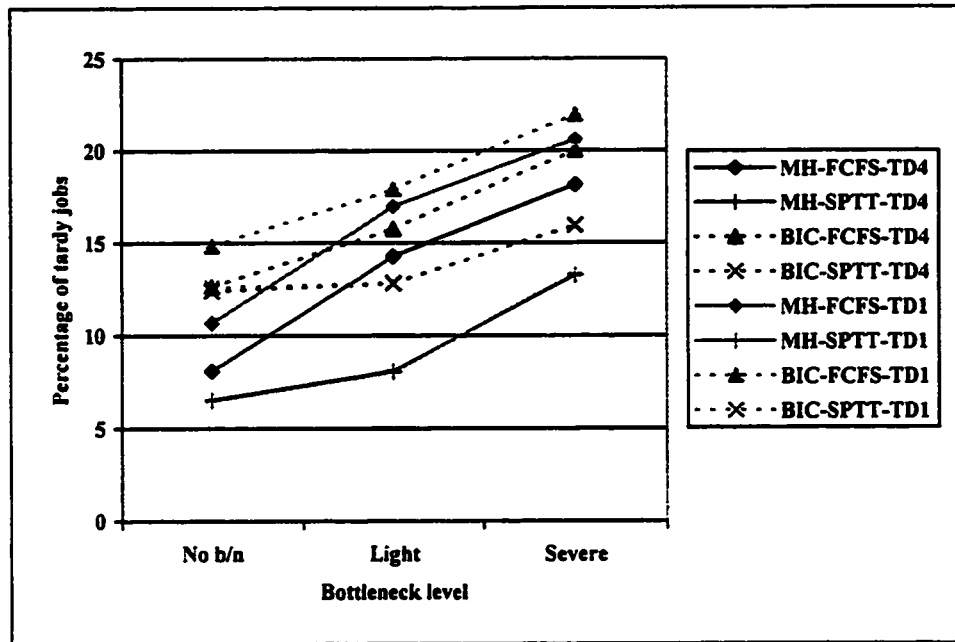


Figure 33: Percentage of tardy jobs (TD1, TD4) in the flowshop without BNPR

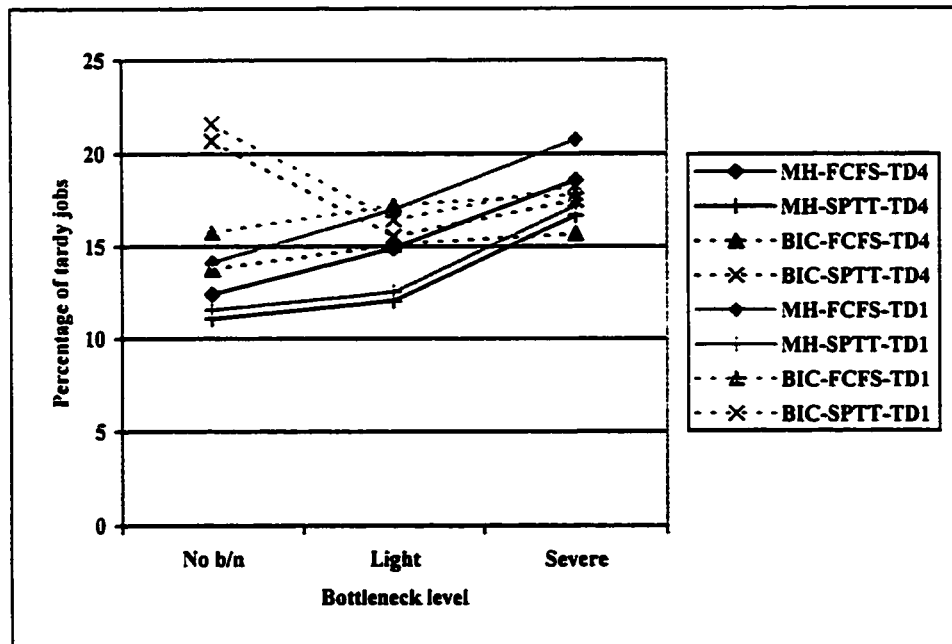


Figure 34: Percentage of tardy jobs (TD1, TD4) in the flowshop with BNPR

The graphs show that the PPW rule performs slightly better than the TWK rule, since for the same mean planned leadtimes, the PPW tardiness measures are generally smaller than the TWK ones. Note that this is not true when SPTT is used without BNPR. For a few combinations of settings, paired t-tests have been carried out, and confirm these observations. When SPTT is used without BNPR, to be more effective, the due date setting rules should take into account the processing time of each operation separately rather than the total processing time.

The results of the ANOVA are given in Table 25 for MT3, in Table 26 for MT6, in Table 27 for TD3 and in Table 28 for TD6. Only partial results are given here, since the results for all three k parameter values are comparable. The looser the due dates are, the lower is the significance of both main factors and interactions. As for the graphs, the ANOVA results are very comparable to the ANOVA leadtime results. However, the dispatch rule does not have as much influence on the tardiness measure as it had on the leadtime measure.

Source	DF	SS	MS	F	P
NRep	19	274.5634	14.4507	37.88	0.000
RS	1	15.1621	15.1621	39.75	0.000
B/N	2	14.9501	7.4750	19.60	0.000
BNPR	1	1.9165	1.9165	5.02	0.025
DR	1	6.6247	6.6247	17.37	0.000
RS*B/N	2	1.1620	0.5810	1.52	0.219
RS*BNPR	1	1.7053	1.7053	4.47	0.035
RS*DR	1	1.2679	1.2679	3.32	0.069
B/N*BNPR	2	5.2754	2.6377	6.92	0.001
B/N*DR	2	3.1568	1.5784	4.14	0.017
BNPR*DR	1	2.1454	2.1454	5.62	0.018
RS*B/N*BNPR	2	2.4943	1.2472	3.27	0.039
RS*B/N*DR	2	0.7147	0.3573	0.94	0.393
RS*BNPR*DR	1	1.4029	1.4029	3.68	0.056
B/N*BNPR*DR	2	0.6377	0.3188	0.84	0.434
RS*B/N*BNPR*DR	2	0.3124	0.1562	0.41	0.664
Error	437	166.6901	0.3814		
Total	479	500.1815			

Table 25: ANOVA for MT3 in the flowshop

Source	DF	SS	MS	F	P
NRep	19	223.3394	11.7547	32.36	0.000
RS	1	12.9429	12.9429	35.63	0.000
B/N	2	11.7212	5.8606	16.13	0.000
BNPR	1	0.7809	0.7809	2.15	0.143
DR	1	1.2000	1.2000	3.30	0.070
RS*B/N	2	0.5870	0.2935	0.81	0.446
RS*BNPR	1	1.2958	1.2958	3.57	0.060
RS*DR	1	0.8927	0.8927	2.46	0.118
B/N*BNPR	2	4.5553	2.2776	6.27	0.002
B/N*DR	2	1.9071	0.9536	2.62	0.074
BNPR*DR	1	1.4564	1.4564	4.01	0.046
RS*B/N*BNPR	2	2.4010	1.2005	3.30	0.038
RS*B/N*DR	2	0.6902	0.3451	0.95	0.388
RS*BNPR*DR	1	0.9594	0.9594	2.64	0.105
B/N*BNPR*DR	2	0.5307	0.2654	0.73	0.482
RS*B/N*BNPR*DR	2	0.2103	0.1052	0.29	0.749
Error	437	158.7613	0.3633		
Total	479	424.2318			

Table 26: ANOVA for MT6 in the flowshop

Source	DF	SS	MS	F	P
NRep	19	6331.96	333.26	85.37	0.000
RS	1	303.45	303.45	77.74	0.000
B/N	2	371.95	185.97	47.64	0.000
BNPR	1	122.12	122.12	31.28	0.000
DR	1	230.06	230.06	58.94	0.000
RS*B/N	2	76.00	38.00	9.73	0.000
RS*BNPR	1	46.79	46.79	11.99	0.001
RS*DR	1	65.97	65.97	16.90	0.000
B/N*BNPR	2	105.07	52.53	13.46	0.000
B/N*DR	2	87.32	43.66	11.19	0.000
BNPR*DR	1	66.49	66.49	17.03	0.000
RS*B/N*BNPR	2	22.47	11.24	2.88	0.057
RS*B/N*DR	2	12.19	6.09	1.56	0.211
RS*BNPR*DR	1	19.97	19.97	5.12	0.024
B/N*BNPR*DR	2	5.21	2.60	0.67	0.514
RS*B/N*BNPR*DR	2	12.51	6.25	1.60	0.203
Error	437	1705.83	3.90		
Total	479	9585.37			

Table 27: ANOVA for TD3 in the flowshop

Source	DF	SS	MS	F	P
NRep	19	5949.11	313.11	70.58	0.000
RS	1	297.17	297.17	66.99	0.000
B/N	2	290.90	145.45	32.79	0.000
BNPR	1	58.35	58.35	13.15	0.000
DR	1	37.03	37.03	8.35	0.004
RS*B/N	2	54.16	27.08	6.10	0.002
RS*BNPR	1	55.19	55.19	12.44	0.000
RS*DR	1	44.70	44.70	10.08	0.002
B/N*BNPR	2	96.10	48.05	10.83	0.000
B/N*DR	2	60.31	30.15	6.80	0.001
BNPR*DR	1	38.10	38.10	8.59	0.004
RS*B/N*BNPR	2	20.36	10.18	2.29	0.102
RS*B/N*DR	2	12.03	6.01	1.36	0.259
RS*BNPR*DR	1	17.96	17.96	4.05	0.045
B/N*BNPR*DR	2	5.25	2.62	0.59	0.554
RS*B/N*BNPR*DR	2	10.17	5.08	1.15	0.319
Error	437	1938.69	4.44		
Total	479	8985.57			

Table 28: ANOVA for TD6 in the flowshop

8.4.2. The jobshop

The mean tardiness results for the jobshop are presented in Table 29. In Table 30, the percentages of tardy jobs are given. The results are illustrated in Figure 35 and Figure 36 for the mean tardiness, and in Figure 37 and Figure 38 for the percentage of tardy jobs. As for the flowshop, the PPW rule performs better than the TWK rule, unless SPTT is used without BNPR. In this case, the two tardiness measures are approximately equal.

					Mean tardiness					
					TWK			PPW		
					<i>Tight</i>	<i>Medium</i>	<i>Loose</i>	<i>Tight</i>	<i>Medium</i>	<i>Loose</i>
RS	B/N	BNPR	DR	N	MT1	MT2	MT3	MT4	MT5	MT6
MH	No	No	FCFS	20	5.501	3.278	1.9480	5.044	2.797	1.5140
MH	No	No	SPTT	20	4.258	2.518	1.4935	4.402	2.557	1.4620
MH	No	Yes	FCFS	20	8.233	5.379	3.4985	7.790	4.845	2.9470
MH	No	Yes	SPTT	20	5.544	3.418	2.1040	5.555	3.355	1.9830
MH	Li	No	FCFS	20	11.774	8.247	5.7000	11.354	7.748	5.1370
MH	Li	No	SPTT	20	8.632	5.752	3.7740	8.742	5.757	3.6855
MH	Li	Yes	FCFS	20	9.367	6.253	4.1365	8.913	5.700	3.5420
MH	Li	Yes	SPTT	20	8.265	5.428	3.5295	8.255	5.323	3.3445
MH	Sv	No	FCFS	20	16.507	12.316	9.1075	16.122	11.832	8.5350
MH	Sv	No	SPTT	20	12.927	9.270	6.5340	13.031	9.271	6.4255
MH	Sv	Yes	FCFS	20	13.811	9.912	7.0370	13.381	9.358	6.3880
MH	Sv	Yes	SPTT	20	12.829	9.196	6.5105	12.814	9.083	6.2930
BIC	No	No	FCFS	20	7.092	4.858	3.3585	6.720	4.496	3.0060
BIC	No	No	SPTT	20	9.006	6.652	4.8895	9.100	6.644	4.8135
BIC	No	Yes	FCFS	20	17.058	13.017	9.9380	16.657	12.534	9.3855
BIC	No	Yes	SPTT	20	15.691	11.961	9.0735	15.648	11.798	8.7960
BIC	Li	No	FCFS	20	9.772	7.080	5.1385	9.462	6.757	4.7980
BIC	Li	No	SPTT	20	7.556	5.316	3.7225	7.701	5.362	3.6925
BIC	Li	Yes	FCFS	20	3.678	2.091	1.1945	3.282	1.716	0.8865
BIC	Li	Yes	SPTT	20	3.934	2.322	1.3895	3.922	2.234	1.2695
BIC	Sv	No	FCFS	20	7.245	4.854	3.2625	6.922	4.511	2.9075
BIC	Sv	No	SPTT	20	5.442	3.562	2.3370	5.641	3.653	2.3495
BIC	Sv	Yes	FCFS	20	4.604	2.704	1.5900	4.189	2.288	1.2270
BIC	Sv	Yes	SPTT	20	4.129	2.444	1.4635	4.171	2.402	1.3720

Table 29: Results summary table for MT in the jobshop

The due dates are relatively tight since the percentage of tardy jobs varies between 6 and 30 percent when the due dates are loose and between 22 to 50 percent when the due dates are tight. Once again, the results are very close to the ones obtained for the actual leadtime. A long leadtime results generally in high tardiness and a short leadtime in low tardiness. However, the graphs in Figure 35 and Figure 37 show that for the BIC strategy in a balanced shop, the tardiness measures are higher when SPTT is used instead of FCFS. This can be observed as well in an unbalanced shop when BNPR is used (see Figure 36 and Figure 38). The effectiveness of SPTT might therefore be controversial regarding tardiness performance.

					Percentage of tardy jobs					
					TWK			PPW		
					<i>Tight</i>	<i>Medium</i>	<i>Loose</i>	<i>Tight</i>	<i>Medium</i>	<i>Loose</i>
RS	B/N	BNPR	DR	N	TD1	TD2	TD3	TD4	TD5	TD6
MH	No	No	FCFS	20	31.205	19.670	12.259	29.443	17.528	9.881
MH	No	No	SPTT	20	23.627	14.488	8.909	24.155	14.702	8.745
MH	No	Yes	FCFS	20	37.843	26.175	17.778	36.745	24.516	15.692
MH	No	Yes	SPTT	20	28.408	18.349	11.727	28.185	18.004	11.230
MH	Li	No	FCFS	20	44.087	32.726	24.226	42.804	31.211	22.713
MH	Li	No	SPTT	20	35.627	25.483	17.942	36.004	25.570	17.674
MH	Li	Yes	FCFS	20	40.433	28.737	20.089	39.301	27.172	18.118
MH	Li	Yes	SPTT	20	35.984	25.241	17.329	35.812	24.937	16.744
MH	Sv	No	FCFS	20	50.292	39.371	30.731	49.275	38.140	29.477
MH	Sv	No	SPTT	20	43.160	33.267	25.350	43.512	33.432	25.152
MH	Sv	Yes	FCFS	20	47.937	36.589	27.548	47.082	35.370	26.131
MH	Sv	Yes	SPTT	20	43.656	33.268	25.089	43.564	33.008	24.715
BIC	No	No	FCFS	20	29.510	19.870	13.833	27.322	18.099	12.424
BIC	No	No	SPTT	20	27.795	20.971	16.125	28.525	21.148	16.013
BIC	No	Yes	FCFS	20	48.525	37.587	29.249	47.465	36.159	27.812
BIC	No	Yes	SPTT	20	43.555	34.138	27.013	43.626	34.129	26.726
BIC	Li	No	FCFS	20	33.692	24.346	18.070	31.920	22.927	16.958
BIC	Li	No	SPTT	20	26.934	19.553	14.239	27.667	19.823	14.298
BIC	Li	Yes	FCFS	20	23.411	13.780	8.112	21.371	11.645	6.134
BIC	Li	Yes	SPTT	20	22.283	13.418	8.046	22.159	13.049	7.468
BIC	Sv	No	FCFS	20	31.201	21.186	14.545	29.452	19.715	13.229
BIC	Sv	No	SPTT	20	23.494	15.755	10.660	24.386	16.224	10.745
BIC	Sv	Yes	FCFS	20	27.163	16.615	10.154	25.208	14.491	8.066
BIC	Sv	Yes	SPTT	20	22.937	13.947	8.460	23.031	13.808	8.005

Table 30: Results summary table for TD in the jobshop

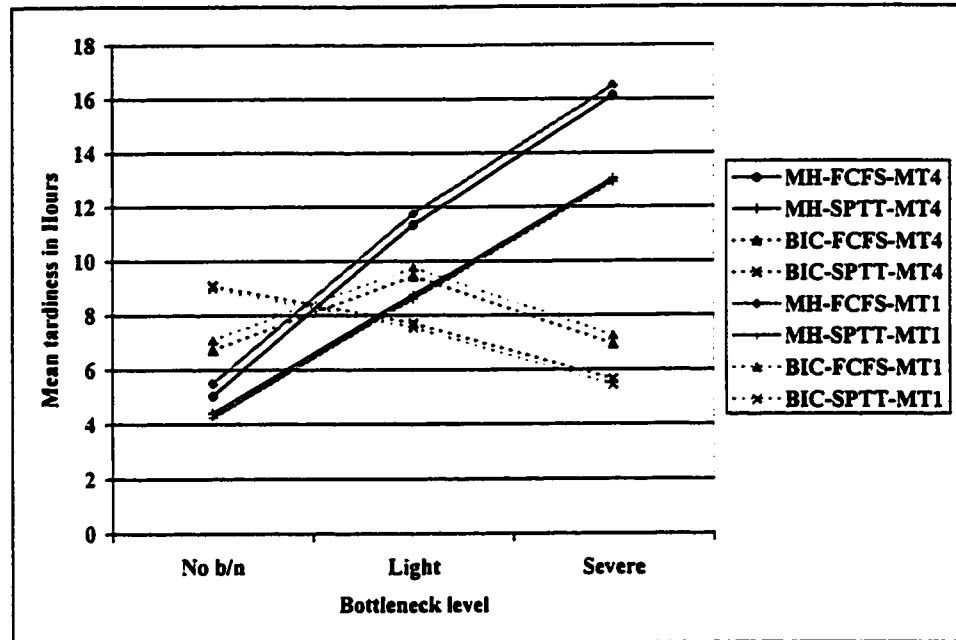


Figure 35: Mean Tardiness (MT1, MT4) in the jobshop without BNPR

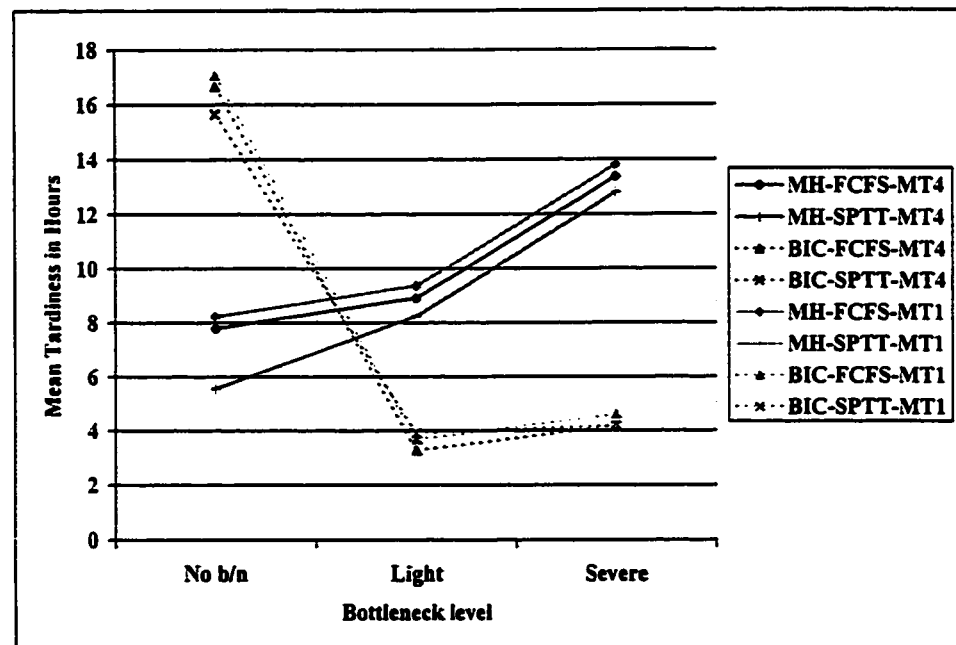


Figure 36: Mean tardiness (MT1, MT4) in the jobshop with BNPR

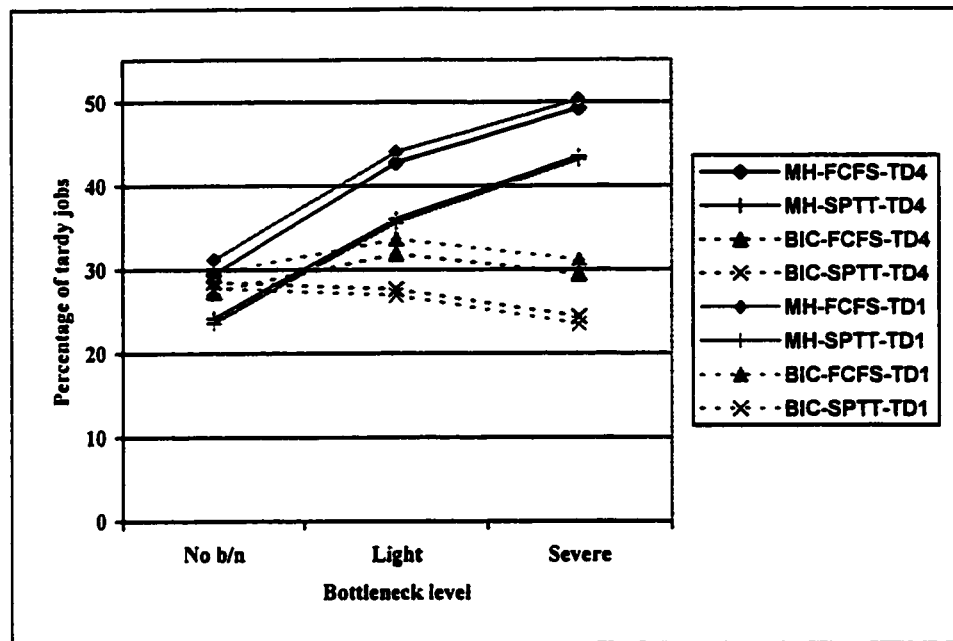


Figure 37: Percentage of tardy jobs (TD4, TD1) in the jobshop without BNPR

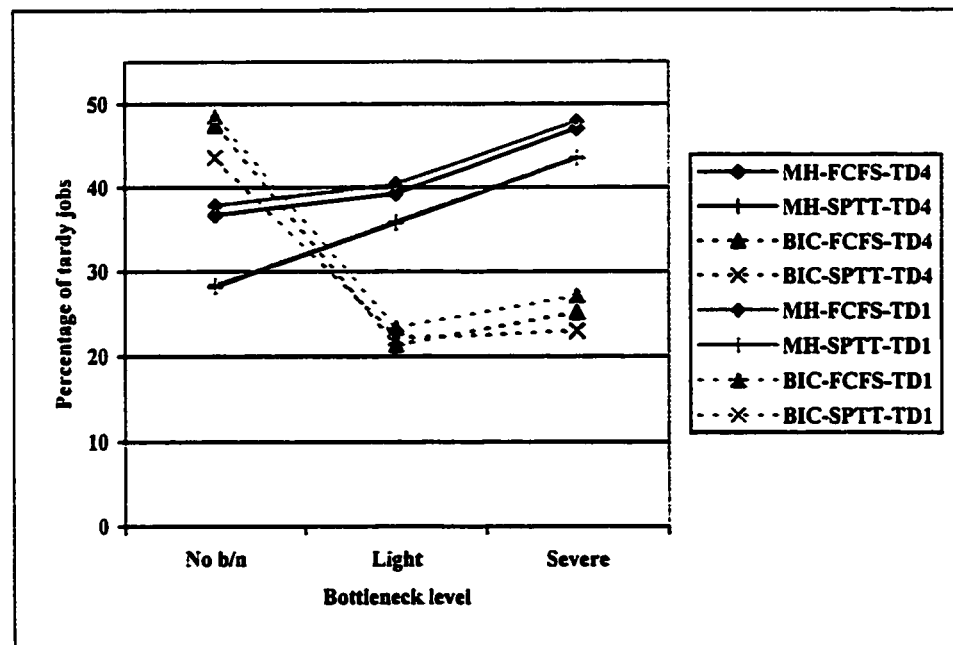


Figure 38: Percentage of tardy jobs (TD1, TD4) in the jobshop with BNPR

Partial results of the ANOVA for the jobshop are given in Table 31 and Table 32. Again, all the results are very similar for both due-date setting rules. The ANOVA results are also very similar to the ones of the leadtime. However, the ANOVA results show that the tardiness measures are not heavily influenced by the dispatch rule chosen. Since the average leadtimes measures were lower for SPTT, it can be concluded that some longer leadtimes observations are occurring when SPTT is used than when FCFS is used.

Source	DF	SS	MS	F	P
NRep	19	4306.67	226.67	34.94	0.000
RS	1	38.00	38.00	5.86	0.016
B/N	2	119.28	59.64	9.19	0.000
BNPR	1	0.66	0.66	0.10	0.749
DR	1	19.10	19.10	2.94	0.087
RS*B/N	2	1823.31	911.65	140.55	0.000
RS*BNPR	1	10.99	10.99	1.69	0.194
RS*DR	1	20.44	20.44	3.15	0.077
B/N*BNPR	2	610.50	305.25	47.06	0.000
B/N*DR	2	12.19	6.10	0.94	0.391
BNPR*DR	1	3.86	3.86	0.59	0.441
RS*B/N*BNPR	2	214.47	107.24	16.53	0.000
RS*B/N*DR	2	2.21	1.11	0.17	0.843
RS*BNPR*DR	1	5.47	5.47	0.84	0.359
B/N*BNPR*DR	2	60.78	30.39	4.69	0.010
RS*B/N*BNPR*DR	2	4.48	2.24	0.35	0.708
Error	437	2834.57	6.49		
Total	479	10086.98			

Table 31: ANOVA for MT6 in the jobshop

Source	DF	SS	MS	F	P
NRep	19	38207.8	2010.9	69.66	0.000
RS	1	2841.4	2841.4	98.43	0.000
B/N	2	837.9	418.9	14.51	0.000
BNPR	1	0.2	0.2	0.01	0.937
DR	1	304.7	304.7	10.56	0.001
RS*B/N	2	13672.7	6836.3	236.82	0.000
RS*BNPR	1	2.0	2.0	0.07	0.792
RS*DR	1	223.7	223.7	7.75	0.006
B/N*BNPR	2	4642.2	2321.1	80.41	0.000
B/N*DR	2	40.7	20.3	0.70	0.495
BNPR*DR	1	20.8	20.8	0.72	0.397
RS*B/N*BNPR	2	1200.6	600.3	20.80	0.000
RS*B/N*DR	2	30.6	15.3	0.53	0.589
RS*BNPR*DR	1	1.9	1.9	0.07	0.798
B/N*BNPR*DR	2	357.0	178.5	6.18	0.002
RS*B/N*BNPR*DR	2	3.5	1.8	0.06	0.941
Error	437	12614.8	28.9		
Total	479	75002.4			

Table 32: ANOVA for TD6 in the jobshop

8.4.3. Summary

The two due date setting rules produce comparable tardiness results. These follow the same trends as the actual leadtime. When the actual leadtime is long, the tardiness measures are high, and when the actual leadtime is short, the tardiness measures are low. The PPW rule performs slightly better than the TWK rule. This is not surprising, since the waiting time in a queue is independent of the processing time of the job, at least when FCFS is used. The PPW takes into account the number of times a job has to wait in a queue, whereas the TWK rule does not. The use of SPTT results in higher tardiness sometimes. Despite the high value of the planned leadtime, the tardiness measures are quite high. To be more effective, the due dates should be set by taking other factors into account. For example, the length of the input buffer is an important element to consider

in making due date setting rules decisions. As well, the bottleneck and non-bottleneck jobs should be given different planned leadtimes.

8.5. Discussion

The analysis has helped in gaining some insight regarding the two order release strategies. Their effectiveness depends essentially on two factors, the flow pattern and the importance of the bottleneck in the shop. The experimental results show that the two strategies do not yield the same results in the flowshop and in the jobshop. The MH strategy works better in the flowshop than in the jobshop and when the shop is balanced. On the contrary, the BIC strategy works better in the jobshop than in the flowshop. The BIC strategy also performs better when a bottleneck exists in the shop. It is important to understand why this happens.

When the flow is sequential, all the jobs go from the first machine to the last in the same order. If no new jobs are released over a period of time, the workload gradually shifts towards the downstream machines, and then decreases. If the total workload is controlled, as in the MH strategy, new releases happen when the first machines are less busy. Therefore the workload at the different work centers is relatively stable when the MH strategy is used. If only the jobs that go through the bottleneck are controlled, as in the BIC strategy, the flow of jobs is split in two: the flow of bottleneck jobs (flow A) and the flow of non-bottleneck jobs (flow B). Flow A is controlled, and since all the jobs follow the same order on the machines, the workload resulting from flow A at the

different machines should be relatively stable over time. However, flow B is not controlled, and since there is a significant variation in the interarrival times for this flow, the workload at the different machines can be substantially affected over time.

The proportion of the work content between bottleneck and non-bottleneck jobs changes as the mean processing time on the bottleneck machine increases. When the shop is balanced, the work content ratio of bottleneck jobs over non-bottleneck jobs is higher than when the shop is not balanced. When the shop is unbalanced, the difference in the performance between the BIC strategy and the MH strategy decreases, since the work content of the non-bottleneck jobs is not as important. Moreover, with the BIC strategy, the bottleneck and non-bottleneck jobs are released independently of one another. When a bottleneck exists in the shop, the non-bottleneck machines can process more jobs than the bottleneck machine. Therefore it is important to maintain a mix of bottleneck and non-bottleneck jobs in the shop. With the MH strategy, there is no control over the proportion of bottleneck and non-bottleneck jobs in the shop. In other words, for a shop with a sequential flow, an effective release strategy should control the total workload. When a bottleneck exists in the shop, the release of bottleneck and non-bottleneck jobs should happen in parallel, so that a constant proportion of bottleneck and non-bottleneck jobs can be maintained in the shop. This suggests a more complex strategy should be developed, which has separate control limits for each category of jobs and which maintains a balance between bottleneck and non-bottleneck jobs.

When the flow is not sequential, there is more confusion on the shop floor. Routing variability is also introduced since not all the routings are identical. It is then

very difficult to regulate the workload at each machine. As a consequence, a higher level of WIP must be maintained in the shop to achieve the same throughput. This can be observed in the experimental results. The WIP in the jobshop is higher than the WIP in the flowshop. Since the flow is not unidirectional, the load at each work center can change rapidly. The control of the aggregate workload does not regulate the load at each machine. In fact, releasing new jobs when the shop load is low does not guarantee that idle machines receive work. On the contrary, the release might just overload machines that are already busy.

The BIC strategy is more robust regarding the flow pattern. When the shop load is balanced there is no merit in regulating work based on the flow to an arbitrary machine. In this case it will perform worse than the MH strategy. However, as soon as a bottleneck exists in the shop, the BIC strategy is effective. With this strategy, the workload is controlled for only the bottleneck center. However, this machine is the most heavily loaded machine, and the longest queues (especially in the jobshop) will appear at this machine. Therefore it is very important to make sure that this machine is as busy as possible by providing it a constant stream of work. At the same time, however, the rate must be controlled to avoid jobs piling up unnecessarily ahead of the bottleneck.

In summary, when the flow of jobs is not sequential and when the shop is not balanced, it is very important to regulate the workload at the bottleneck machine. As well, bottleneck and non-bottleneck jobs should be released in parallel when a bottleneck exists in the shop.

The bottleneck priority rule (BNPR) introduced in this study gives priority to the bottleneck jobs during selection for loading at any machine. This rule is appropriate when the bottleneck machine is much slower than the other machines, or when the time necessary to reach the bottleneck is hard to predict, like in the jobshop. In these cases, the bottleneck jobs can be processed faster, and the non-bottleneck machines still have enough time to process the non-bottleneck jobs in a reasonable period of time.

9. Conclusions and further research

In the past chapters, some of the merits of the MH strategy (see section 3.3.1) and the BIC strategy (see section 3.3.2) were pointed out. In this chapter, the results obtained in this study are summarized. Some suggestions for further research are then given.

9.1. *Summary of the research*

The purpose of this thesis was to study two order release strategies. One is based on the bottleneck needs and the other one controls the aggregate workload in the shop. In particular, the influence of the bottleneck on the effectiveness of these strategies was investigated. As well, the strategies have been compared in two kinds of shops, one with a sequential flow, and the other one with a non-sequential flow.

Operating curves relating the throughput and the WIP were constructed. These curves were useful in determining appropriate levels of WIP and throughput for the statistical comparison of the two strategies. The analysis performed shows that the release strategy based on aggregate control of the Maximum Hours processing time (called MH strategy) is effective in controlling the WIP and the leadtime when the flow is sequential. On the contrary, the MH strategy is less effective in controlling the WIP and the leadtime in a jobshop, when the routing pattern is different for every job. The control of the total workload does not insure that all the machines are adequately loaded when the flow is not

sequential. The Bottleneck Input Control (BIC) strategy is preferable when there is a (severe) bottleneck in the job shop. In this case, the strategy regulates the workload at the most loaded work center. It insures that the bottleneck machine always has work available as much of the time as possible and yet prevents the jobs from piling up in front of this machine.

The results of the study show that it is important to use two separate release mechanisms for the bottleneck and non-bottleneck jobs when a bottleneck exists in the shop. Moreover, it shows that it is important to control the mix of bottleneck and non-bottleneck jobs in the shop.

9.2. *Further research*

This research is limited in that the input control systems studied are very simple. In particular, for the flowshop model, the conclusion of the study suggests the use of a strategy that controls the aggregate workload, and that releases the bottleneck and non-bottleneck jobs in parallel with two separate mechanisms. It would be interesting to implement such a release strategy to find out its effectiveness. For a jobshop, input control based on the bottleneck has proved to be more powerful. Control of the aggregate workload is not very useful since the mix of jobs can change radically in a short period of time. However, several researchers have found that load balancing, based on look ahead dispatch rules for example, results in a less congested shop. The question remains open as to whether load balancing is beneficial with a release strategy based on the bottleneck.

Moreover, no evidence has been provided that a release system based on the bottleneck needs is better than a release system based on load balancing.

The bottleneck release strategy developed in this study can possibly be improved. For example, more principles of the Theory Of Constraints (TOC) could be incorporated in the release decision and in the operation of the shop.

Finally, this research was limited to shops without a planning system. Orders could not be rejected and resource levels were fixed. In this context, important variations of the leadtime are unavoidable. Integrating the strategies developed in this study with a production facility using a planning system might lead to different conclusions.

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Appendix 1. Queuing model results for the flowshop

All the spreadsheet results are given for the flowshop model in pages 152 to 163. Pages 152 to 157 contain the results for the MH strategy, and pages 158 to 163 the results for the BIC strategy. Pages 152 to 154 and 158 to 160 contain the results of the queuing model when the processing time at the dummy machine is 0.2. Pages 155 to 157 and 161 to 163 contain the results of the queuing model when the processing time at the dummy machine is 0.85.

7. BIC strategy, no bottleneck, dummy machine processing time: 0.2

[illegible]

9. BIC strategy, severe bottleneck, dummy machine processing time: 0.2

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Work Flow Analysis Spreadsheet - Eight Machine Shop																		
2	NOTE: This spreadsheet is designed to model the BIC strategy in the RenzShop																		
3	Operation:																		
4	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
5	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
6	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
7	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
8	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
9	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
10	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
11	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
12	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
13	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
14	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
16	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
17	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
18	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
19	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
20	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
21	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
22	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
23	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
24	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
25	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
26	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
27	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
28	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
29	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
30	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
31	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
32	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
33	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
34	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
35	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
36	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
37	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
38	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
39	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
40	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
41	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
42	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
43	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
44	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
45	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
46	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
47	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
48	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
49	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
50	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
51	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
52	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
53	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
54	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
55	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
56	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
57	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
58	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
59	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
60	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
61	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19

Appendix 2. Queuing model results for the jobshop

All the spreadsheet results for the jobshop are given in pages 165 to 168. The results are given only for a severe bottleneck. Pages 165 and 166 contain the results for the MH strategy when the dummy machine processing time is 0.2 and 0.85. Pages 167 and 168 contain the results for the MH strategy when the dummy machine processing time is 0.2 and 0.85.

SIMAN Model

```

62$      [1] CREATE,      1,IntArr:IntArr:MARK(Job release date);

! assigns routings and processing times. P(PTD,1)=1 if dist is Erl, =2 if normal

      ASSIGN:      JobsInSyst=JobsInSyst+1;
                   Nb of tasks=NbTask;
                   Routing(1)=ToNextSt(1);
                   A(1)=1;
                   A(2)=routing(1);
                   Proc Time(A(1))=(P(PTD,1)==1)*P(MPT,A(2))*
                     (1-sqrt(P(k,A(2)))*P(CVP,A(2))):
                   A(3)=(P(PTD,1)==1)*ERLA(P(MPT,A(2))*P(CVP,A(2))
                     /sqrt(P(k,A(2))),P(k,A(2))):
                   Proc Time(A(1))=Proc Time(A(1))+A(3);
                   Proc Time(A(1))=Max(Proc Time(A(1)),(P(PTD,1)==2)
                     *NORM(P(MPT,A(2)),P(MPT,A(2))*P(CVP,A(2))):
                   Proc Time(A(1))=Proc Time(A(1))*P(UL,A(2));
                   ThruBN=(P(BNM,1)==Routing(A(1)))*Proc Time(A(1));
                   Rem Proc Time=Proc Time(A(1));
                   A(1)=2;
60$      WHILE:      A(1) .LE. Max(MXRES*(P(FO,1)==1),Nb of Tasks);
59$      ASSIGN:      Routing(A(1))=ToNextSt(Routing(A(1)-1)+1);
                   A(2)=Routing(A(1));
                   Proc Time(A(1))=(P(PTD,1)==1)*P(MPT,A(2))
                     *(1-sqrt(P(k,A(2)))*P(CVP,A(2))):
                   A(3)=(P(PTD,1)==1)*ERLA(P(MPT,A(2))*P(CVP,A(2))
                     /sqrt(P(k,A(2))),P(k,A(2))):
                   Proc Time(A(1))=Proc Time(A(1))+A(3);
                   Proc Time(A(1))=Max(Proc Time(A(1)),(P(PTD,1)==2)
                     *NORM(P(MPT,A(2)),P(MPT,A(2))*P(CVP,A(2))):
                   Proc Time(A(1))=Proc Time(A(1))*P(UL,A(2));
                   ThruBN=ThruBN+(P(BNM,1)==Routing(A(1)))*Proc Time(A(1));
                   Rem Proc Time=Rem Proc time+Proc Time(A(1));
                   A(1)=A(1)+1;
58$      ENDWHILE;

! If the model is a FLOW shop, then removes some tasks

18$      [2] IF:      P(FO,1)==1;
29$      ASSIGN:      X(1)=MXRES-Nb of tasks;
28$      WHILE:      X(1) .GT. 0;
27$      ASSIGN:      X(2)=ANINT(UNIF(.5,Nb of tasks+X(1)+.5)):
                   ThruBN=ThruBN-(Routing(X(2))==P(BNM,1))*Proc Time(X(2));
                   Rem Proc time=Rem Proc time - Proc Time(X(2));
                   X(1)=X(1)-1;
26$      WHILE:      X(2) .LE. Nb of tasks+X(1);
25$      ASSIGN:      Routing(X(2))=Routing(X(2)+1);
                   Proc time(X(2))=Proc Time(X(2)+1);
                   X(2)=X(2)+1;
24$      ENDWHILE;
23$      ENDWHILE;
17$      ENDIF;

! The job is ready to enter the shop, due date is assigned

57$      [3] ASSIGN:      Due Date=Rem Proc Time;
                   Due Date=
                   TNOW+Nb of Tasks*(P(DDSR,1)==0)+
                   Due Date*P(PPW,1)*(P(DDSR,1)==1)+
                   (Due Date+(PPW,1)*Nb Of tasks)*(P(DDSR,1)==2)
                   :

```

```

Routing(Nb of tasks+1)=7:
M=Routing(1);

! Depending on the release strategy chosen, the jobs is either released or sent
! to the input buffer

56$      [4]  BRANCH,      1:If,P(RS,1)==0,8$,Yes:
                                If,P(RS,1)==1,55$,Yes:
                                Else,16$,Yes;      RS==1: Aggregate input control,
                                !else DBR

55$      BRANCH,      1:If,WIP .LT. P(MaxHours,1),8$,Yes:
                                Else,54$,Yes;      Is the shop full?

16$      BRANCH,      1:If,(BNQ Length .LT. P(MaxHours,1)) .OR. (ThruBN==0),
                                8$,Yes:
                                Else,54$,Yes;      Is the bottleneck queue full?

54$      QUEUE,      InputBuffer:DETACH;

! the job goes to the shop

8$      ASSIGN:      BNQ Length=BNQ Length+ThruBN:
                                WIP=WIP+Rem Proc Time:NEXT(ToShop);

ToShop   [5]  TALLY:      WTimeInput,INT(Job release date),1;
38$      ASSIGN:      CurrTask Due Date=TNOW:
                                JobsInShop=JobsInShop+1;
44$      ROUTE:      0.0,Routing(1):MARK(Job Release Shop);

52$      STATION,      StationSet;

Next task  BRANCH,      3:Always,53$,Yes:
                                If,MR(M)==0,Queue mgt,Yes:
                                If,MR(M)==0,Turn On,Yes:
53$      ASSIGN:      Actual task=Actual task +1:
                                SetIndex=MemIdx(StationSet,M):
                                CurrTask Due Date=
                                CurrTask Due Date+(P(DDSR,1)==0)+(P(DDSR,1)==1)
                                *Proc Time(A(27))*P(PFW,1)+(P(DDSR,1)==2)*(P(PFW,1)
                                +Proc Time(A(27))):MARK(Arrival In Queue);

QueueStation  QUEUE, [6]  QueueSet(SetIndex);
51$      SEIZE,      1:MachineSet(SetIndex),1;
15$      ASSIGN:      BNQ Length=BNQ Length - (P(BNM,1)==M)*ThruBN:
                                WIP=WIP - Proc Time(Actual task):
                                AggUL =AggUL+1/6:
                                ThruBN= ThruBN-Proc Time(Actual task)*(P(BNM,1)==M));
14$      BRANCH,      3:Always,20$,Yes:
                                If,(WIP .LT. P(MaxHours,1)) .AND. (P(RS,1)==1)
                                .AND. (NQ(InputBuffer) .GT. 0),CheckInput1,Yes:
                                ! a new job can enter the shop
                                If,(P(BNM,1)==M) .AND. (P(RS,1)==2),CheckInput2,Yes:
                                ! check if the BNQ Length is below a certain
                                ! level and if some jobs can be released
20$      TALLY:      M+12,INT(Arrival in queue),1;
50$      DELAY:      Proc Time(Actual task):MARK(A(1));
21$      TALLY:      M+18,INT(A(1)),1;
48$      ASSIGN:      MR(M)=0:
                                AggUL= AggUL-1/6:
                                Rem Proc Time=Rem Proc Time - Proc time(Actual task);
49$      RELEASE:      MachineSet(SetIndex),1;
45$      BRANCH,      3:Always,46$,Yes:
                                If,NQ(M) .GT. 0,Queue mgt,Yes:
                                If,NQ(M) .GT. 0,Turn On,Yes:
46$      ROUTE:      0.0,Routing(Actual task+1);
Queue mgt  BRANCH,      1:If,P(DR,1)==1,37$,Yes: !FCFS

```

```

                                If, P(DR,1)==2,36$, Yes: !SPTT
                                If, P(DR,1)==3,35$, Yes: !EDD
                                If, P(DR,1)==4,34$, Yes: !SCR
                                If, P(DR,1)==5,33$, Yes: !ODD
                                If, P(DR,1)==6,32$, Yes: !OCR
37$      [7]  SEARCH,          M,1,NQ:MIN(Arrival in queue-TNOW
                                -(P(PBN,1)==1)*(ThruBN .GT. 0)*1000);
31$      REMOVE:              J,M,30$;
47$      DISPOSE;
30$      INSERT:              QueueStation,1;

! chooses the next job to be processed, depending on the release strategy chosen

36$      SEARCH,              M,1,NQ:MIN(Proc Time(Actual task)/1000
                                +min(0,(P(MWT,1)+Arrival in queue-TNOW)*100)
                                -(P(PBN,1)==1)*(ThruBN .GT. 0)*1000):NEXT(31$);
35$      SEARCH,              M,1,NQ:MIN(Due Date-(P(PBN,1)==1)
                                *(ThruBN .GT. 0)*1000):NEXT(31$);
34$      SEARCH,              M,1,NQ:MIN((Due Date-TNOW)/Rem Proc Time-
                                10000 -(P(PBN,1)==1)*(ThruBN .GT. 0)*1000):
                                NEXT(31$);
33$      SEARCH,              M,1,NQ:Min(CurrTask Due Date-(P(PBN,1)==1)
                                *(ThruBN .GT. 0)*1000-(P(PBN,1)==1)
                                *(ThruBN .GT. 0)*1000):NEXT(31$);
32$      SEARCH,              M,1,NQ:MIN((CurrTask Due Date-TNOW)/Proc Time(Actual Task)
                                -10000-(P(PBN,1)==1)*(ThruBN .GT. 0)*1000):NEXT(31$);
Turn On  ASSIGN:              MR(M)=1:NEXT(47$);

! Check how many jobs to release depending on the strategy chosen 1=Aggregate control,
! 2= b/n str.

CheckInput1  ASSIGN: [8]      X(1)=0;
                                WHILE:      (WIP .LT. P(MaxHours,1)).AND. (NQ(InputBuffer) .GT. X(1));
                                ASSIGN:      X(1)=X(1)+1;
                                                WIP=WIP+AQUE(InputBuffer,X(1),29);
                                                BNQ Length=BNQ Length+AQUE(InputBuffer,X(1),32);
                                ENDWHILE;
                                WHILE:      X(1) .GT. 0;
                                REMOVE:      X(1),InputBuffer,ToShop;
                                ASSIGN:      X(1)=X(1)-1;
                                ENDWHILE;
                                DISPOSE;

CheckInput2  ASSIGN:          X(1)=0;
10$          WHILE:          (BNQ Length .LT. P(MaxHours,1)).AND. (NQ(InputBuffer)
                                .GT. X(1));
7$          ASSIGN:          X(1)=X(1)+1;
                                BNQ Length=BNQ Length+AQUE(InputBuffer,X(1),32);
                                WIP =WIP+AQUE(InputBuffer,X(1),29);
9$          ENDWHILE;
6$          WHILE:          X(1) .GT. 0;
13$         REMOVE:          X(1),InputBuffer,ToShop;
5$          ASSIGN:          X(1)=X(1)-1;
4$          ENDWHILE;
12$         DISPOSE;

! collects statistics

43$      [9]  STATION,        ExitStation;
42$      ASSIGN:              JobsInSyst=JobsInSyst-1;
                                JobsInShop=JobsInShop-1;
                                FlowTimeOp=(Tnow-Job release shop)/Nb of tasks;
                                FlowTimeO,FlowTimeOp,1;
41$      TALLY:              FlowTimeSh,INT(Job release shop),1;
22$      TALLY:              LeadTime,INT(Job release date),1;
19$      TALLY:              MLateness,TNOW-Due Date,1;
3$       TALLY:              MTardiness,Max(0,TNOW-Due Date),1;
2$       TALLY:
1$       COUNT:              Tardy jobs,(TNOW .GT. Due Date);

```

```

40$ COUNT: Jobs done,1;
39$ DISPOSE;

! Writes the results of the experiment in the outputfile

[9A] CREATE, 1,6500:,1;
WRITE, EXPERIMENT,"(1X,7(F3.0,1X),3(F6.2,1X),
(F6.0,1X),8(F6.2,1X),(F6.3,1X))":
NRep,2-P(FO,1),P(RS,1),
((P(UL,4)-P(UL,1)) .GT. 0)
+ ((P(UL,4)-P(UL,1)) .GT. 0.55)+1,
P(PBN,1)+1,P(DR,1),
(P(CVP,1)==0.3)+2*(P(CVP,1)==0.5),
P(MaxHours,1),
DAVG(TotJobs),
DAVG(NbJobsSh),
NC(Jobs Done),
TAVG(FlowTimeO),
TAVG(FlowTimeSh),
TAVG(Leadtime),
TAVG(MTardiness),
TAVG(MLateness),
NC(Tardy Jobs)/NC(Jobs Done)*100,
DAVG(WIProc),
DAVG(BNLength),
DAVG(AggrUL);

DISPOSE;

```

Appendix 3.SIMAN experiment file

```

PROJECT,      Job shop,mpc,11/11/96,Yes;

BEGIN,        Yes,No;

; the first 8 attributes are temporary attributes.

ATTRIBUTES:   1,Temporaryatt(8):
               9,SetIndex:! is equal to the station number the piece has entered
              10,Job release date,0:! time of creation of the job
              11,Job Release Shop:! time the job is released in the shop
              12,Arrival In Queue:! time of arrival in the last queue
              13,Nb of tasks:
              14,Routing(7):! transition matrix
              21,Proc Time(6):
              27,Actual task:
              28,Due Date,0:
              29,Rem Proc Time:
              30,Priority:!not used currently
              31,CurrTask Due Date,0:
              32,ThruBN,0;! is equal to the processing time at the B/n

!Creates the outputfile for all the replications

FILES:        1,EXPERIMENT,"f1o12112.d20",Sequential(),Free Format,Error,No,Hold;

[10]
PARAMETERS:   1,Marr,0.9: !interarrival mean
              2,NbT,0,1,0,2,0,3,0.3333333333,4,0.666666666666666,5,1,6:!number of tasks
              3,R1,0,1,1,2,0,3,0,4,0,5,0,6,0,7:! transition prob from machine1 to another
              4,R2,0,1,0,2,1,3,0,4,0,5,0,6,0,7:
              5,R3,0,1,0,2,0,3,1,4,0,5,0,6,0,7:
              6,R4,0,1,0,2,0,3,0,4,1,5,0,6,0,7:
              7,R5,0,1,0,2,0,3,0,4,0,5,1,6,0,7:
              8,R6,0,1,0,2,0,3,0,4,0,5,0,6,1,7:
              9,ROut,1,1,0,2,0,3,0,4,0,5,0,6,0,7:! transition prob to enter the system
              10,MPT,1,1,1,1,1,1:
              11,CVP,0.5,0.5,0.5,0.5,0.5,0.5:
              12,k,2,2,2,2,2:
              13,PTD,1:
              14,UL,0.93,0.93,0.93,1.05,0.93,0.93:
              15,PPW,6:
              16,DDSR,1:
              17,DR,1:
              18,RS,1:
              19,MaxHours,80:
              20,MWT,15:
              21,FO,1:
              22,BNM,4:
              23,PBN,0;!is equal to 1 if the jobs that go thru BN have queue pr.
                  !0 otherwise

[11]
VARIABLES:    10,JobsInSyst,0: !counts all the jobs in the system
              11,JobsInShop: ! counts the number of jobs in the shop
              12,FlowTimeOp: ! used to compute the flow time per operation
              13,WIP,0: ! WIP given in hours in the shop minus the processing times
                  ! of the current operations
              14,BNQ Length,0: ! Number of hours of processing for the b/n machine,
                  ! for the jobs en route to the b/n

```

```

15,AggUL;

[12]
SEEDS:      1,,Common:
            2,,Common:
            3,,Common:
            4,,Common:
            5,,Common:
            6,,Common:
            7,,Common:
            8,,Common:
            9,,Common;

QUEUES:     1,MachineQ1,FIFO:
            2,MachineQ2,FIFO:
            3,MachineQ3,FIFO:
            4,MachineQ4,FIFO:
            5,MachineQ5,FIFO:
            6,MachineQ6,FIFO:
            8,InputBuffer,FIFO;

RESOURCES:  1,Machine1,Capacity(0,):
            2,Machine2,Capacity(0,):
            3,Machine3,Capacity(0,):
            4,Machine4,Capacity(0,):
            5,Machine5,Capacity(0,):
            6,Machine6,Capacity(0,);

STATIONS:   1,Station1:
            2,Station2:
            3,Station3:
            4,Station4:
            5,Station5:
            6,Station6:
            7,ExitStation;

COUNTERS:   10,Jobs done,,Replicate:
            11,Tardy jobs,,Replicate;

[13]
TALLIES:     10,FlowTimeO, "FltOp1.flw":
            11,FlowTimeSh, "FltSh.flw":
            12,LeadTime, "Ltime.flw":
            13,WTime1:
            14,WTime2:
            15,WTime3:
            16,WTime4:
            17,WTime5:
            18,WTime6:
            19,PTime1:
            20,PTime2:
            21,PTime3:
            22,PTime4:
            23,PTime5:
            24,PTime6:
            25,WTimeInput:
            26,MTardiness:
            27,MLateness;

DSTATS:     NQ(InputBuffer),Buffer length:
            JobsInSyst,TotJobs:
            JobsInShop,NbjobsSh:
            AggUL,AggrUL:
            WIP, WIProc:
            BNQ Length, BNLength:
            NR(Machine1)*100,Machine1 Util:
            NR(Machine2)*100,Machine2 Util:
            NR(Machine3)*100,Machine3 Util:

```



```

NR(Machine4)*100,Machine4 Util:
NR(Machine5)*100,Machine5 Util:
NR(Machine6)*100,Machine6 Util:
NQ(MachineQ1),Queue1 Length:
NQ(MachineQ2),Queue2 Length:
NQ(MachineQ3),Queue3 length:
NQ(MachineQ4),Queue4 length:
NQ(MachineQ5),Queue5 Length:
NQ(MachineQ6),Queue6 Length;

OUTPUTS:  DAVG(Machine1 Util):
          DAVG(Machine2 Util):
          DAVG(Machine3 Util):
          DAVG(Machine4 Util):
          DAVG(Machine5 Util):
          DAVG(Machine6 Util):
          DAVG(Queue1 length):
          DAVG(Queue2 length):
          DAVG(Queue3 length):
          DAVG(Queue4 length):
          DAVG(Queue5 length):
          DAVG(Queue6 length):
          DAVG(Buffer length):
          TAVG(FlowTimeSh):
          TAVG(WTimeInput):
          TAVG(WTime1): ! Waiting time at a machine
          TAVG(WTime2):
          TAVG(WTime3):
          TAVG(WTime4):
          TAVG(WTime5):
          TAVG(WTime6):
          NC(Jobs Done):
          TAVG(FlowTimeO):
          TAVG(FlowTimeSh):
          TAVG(LeadTime):
          TAVG(MTardiness):
          TAVG(MLateness):
          NC(Tardy Jobs):
          DAVG(TotJobs):
          DAVG(AggrUL):
          DAVG(WIProc):
          DAVG(BNLength):
          DAVG(NbJobsSh);

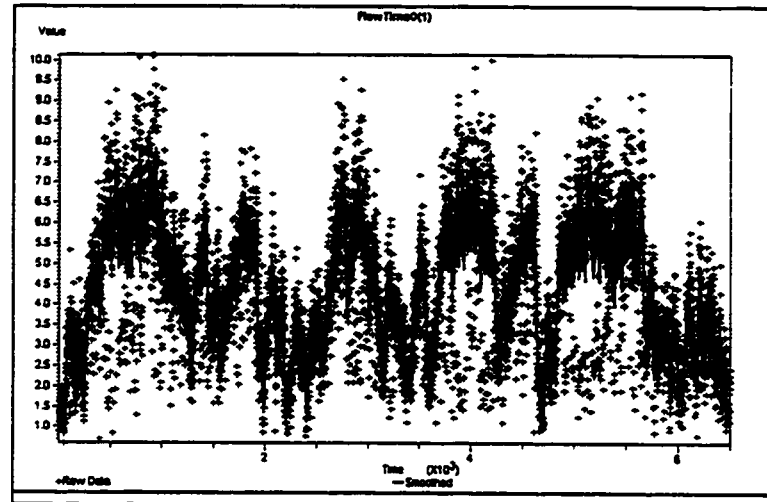
REPLICATE, 1,0.0,6500;

EXPRESSIONS: 1,IntArr,EX(1,1):
              2,NbTask,DP(2,2):
              3,ToNextSt(7),DP(9,3),DP(3,4),DP(4,5),DP(5,6),DP(6,7),DP(7,8),DP(8,9);

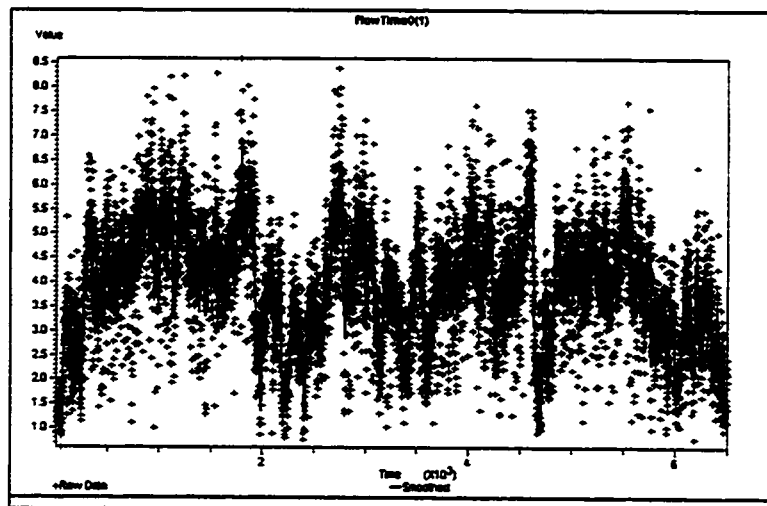
SETS:        StationSet,Station1,Station2,Station3,Station4,Station5,Station6:
              MachineSet,Machine1,Machine2,Machine3,Machine4,Machine5,Machine6:
              QueueSet,MachineQ1,MachineQ2,MachineQ3,MachineQ4,MachineQ5,MachineQ6:

```

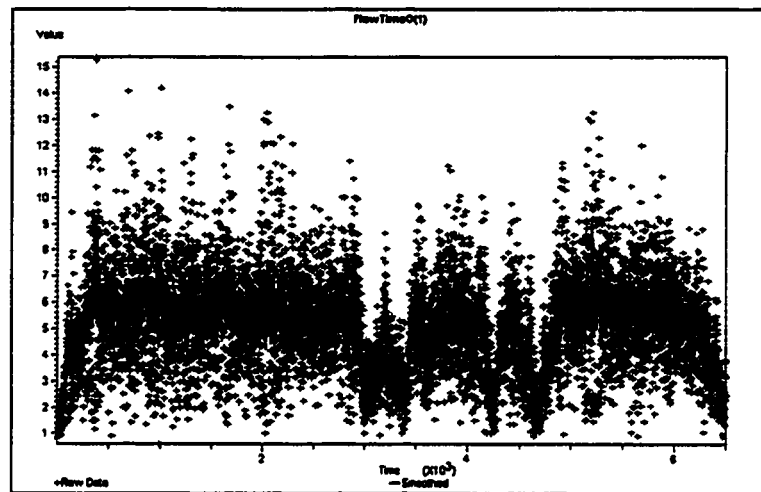
Appendix 4. Moving average of the worst case scenarios



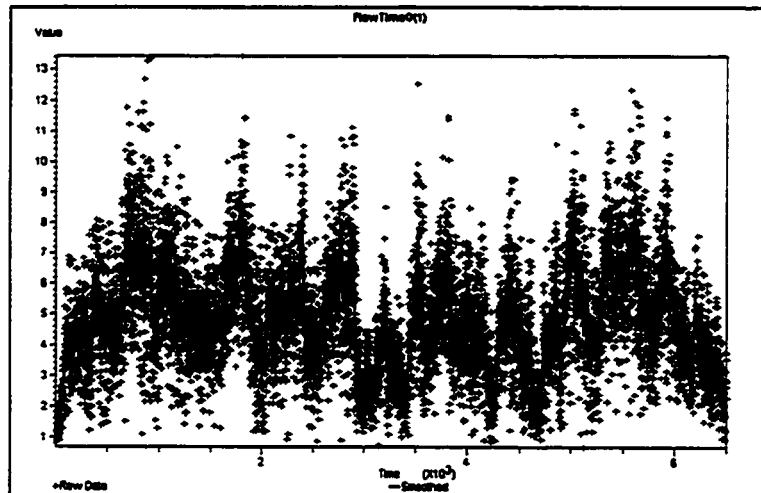
Moving average for the flowshop with an MH strategy



Moving average for the flowshop with a BIC strategy

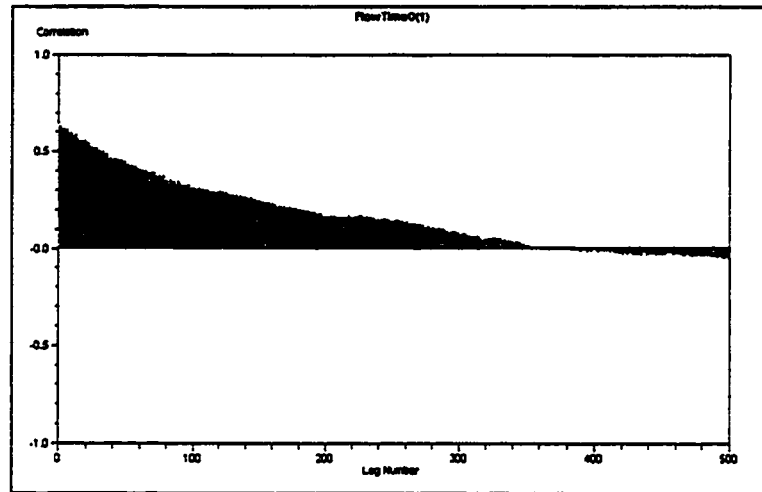


Moving average for the jobshop with the MH strategy

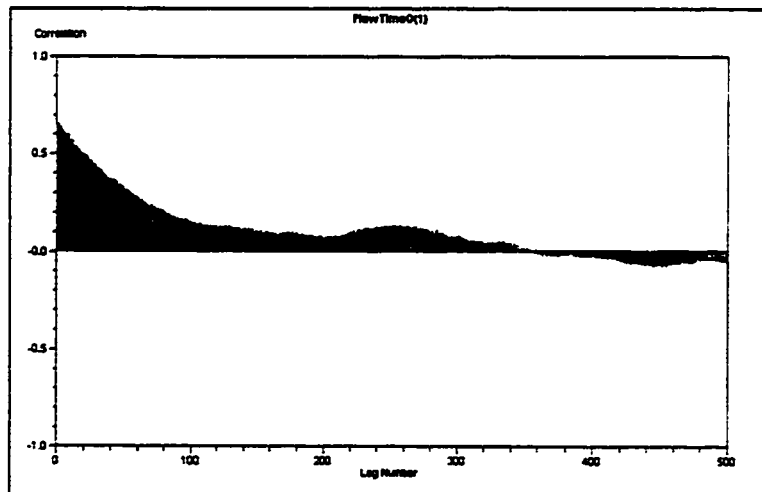


Moving average for the jobshop with the BIC strategy

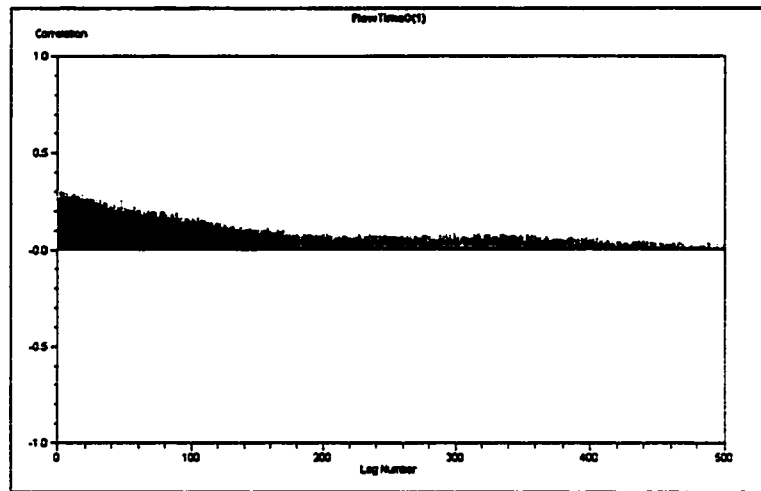
Appendix 5. Correlograms for the worst case scenarios



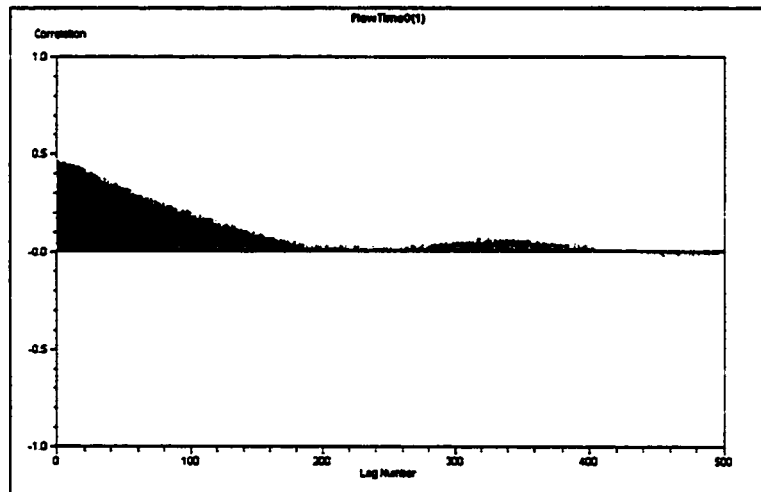
Correlogram for the flowshop with the MH strategy



Correlogram for the flowshop with the BIC strategy



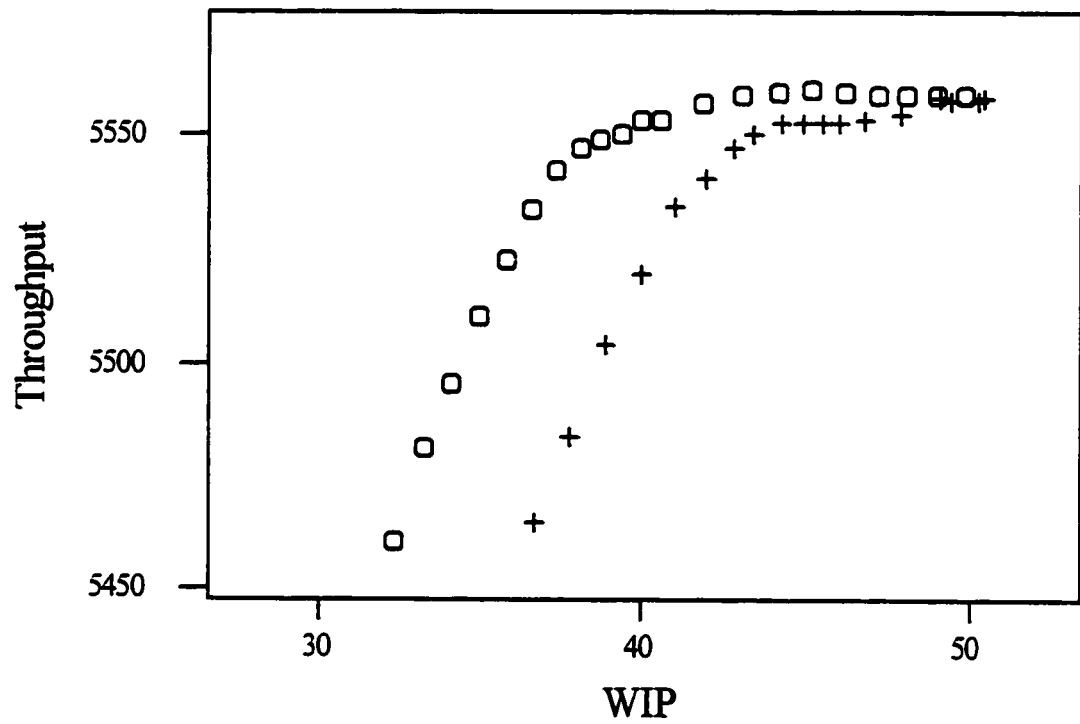
Correlogram for the jobshop with the MH strategy



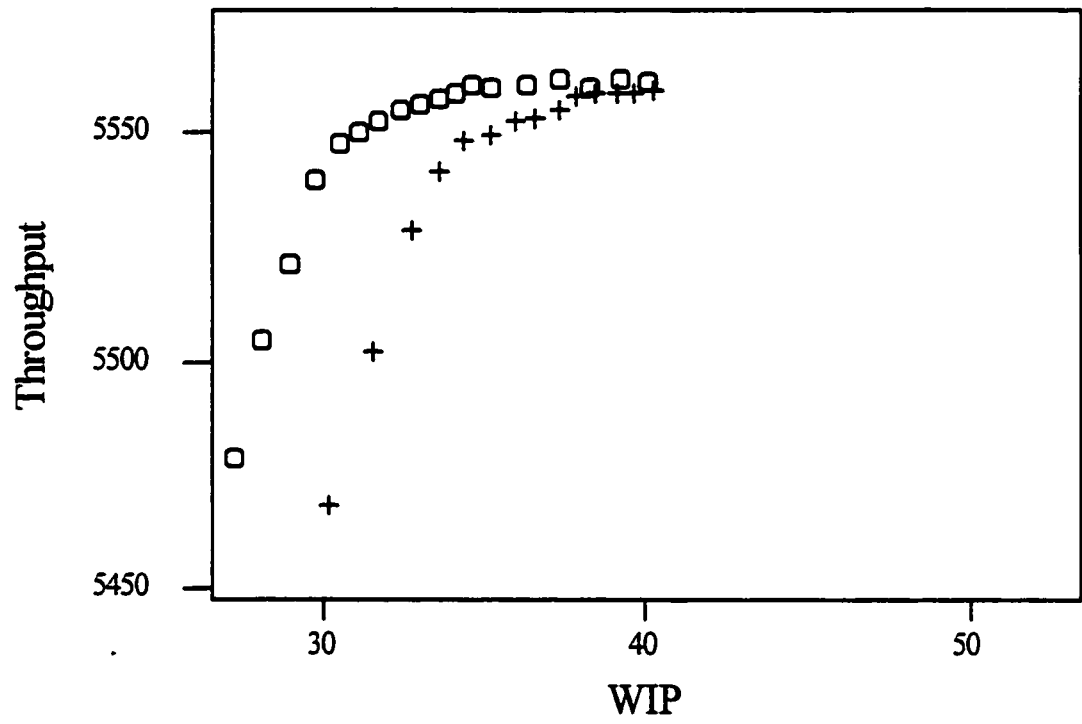
Correlogram for the jobshop with the BIC strategy

Appendix 6. Operating curves for the flowshop

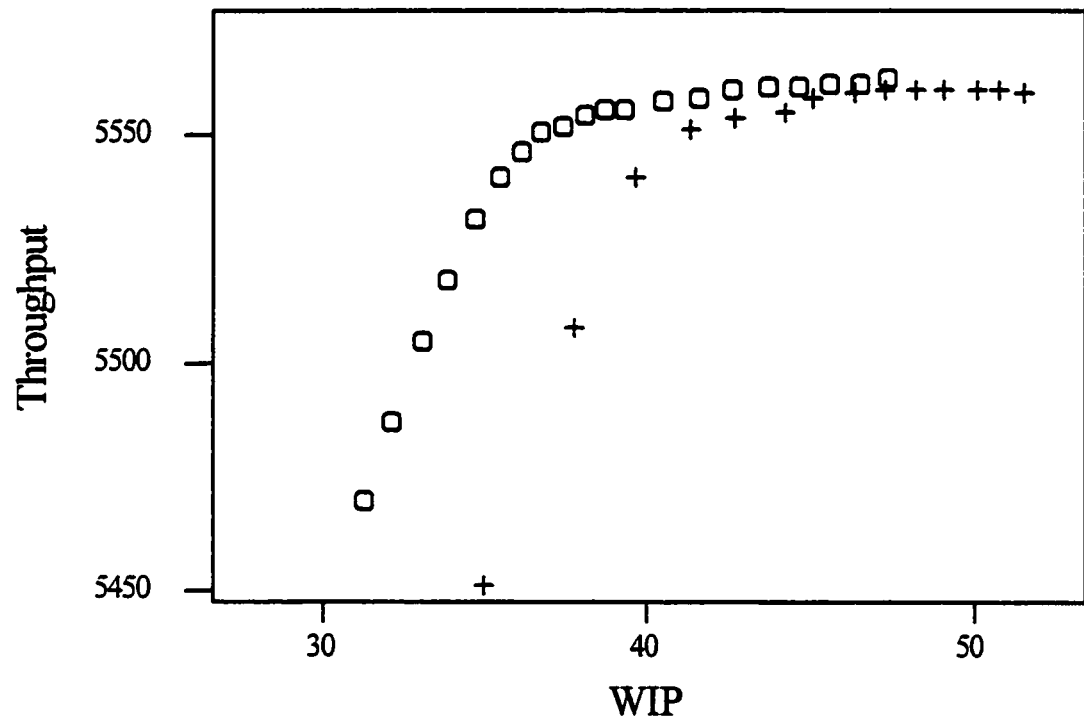
Flowshop; operating curves; 111



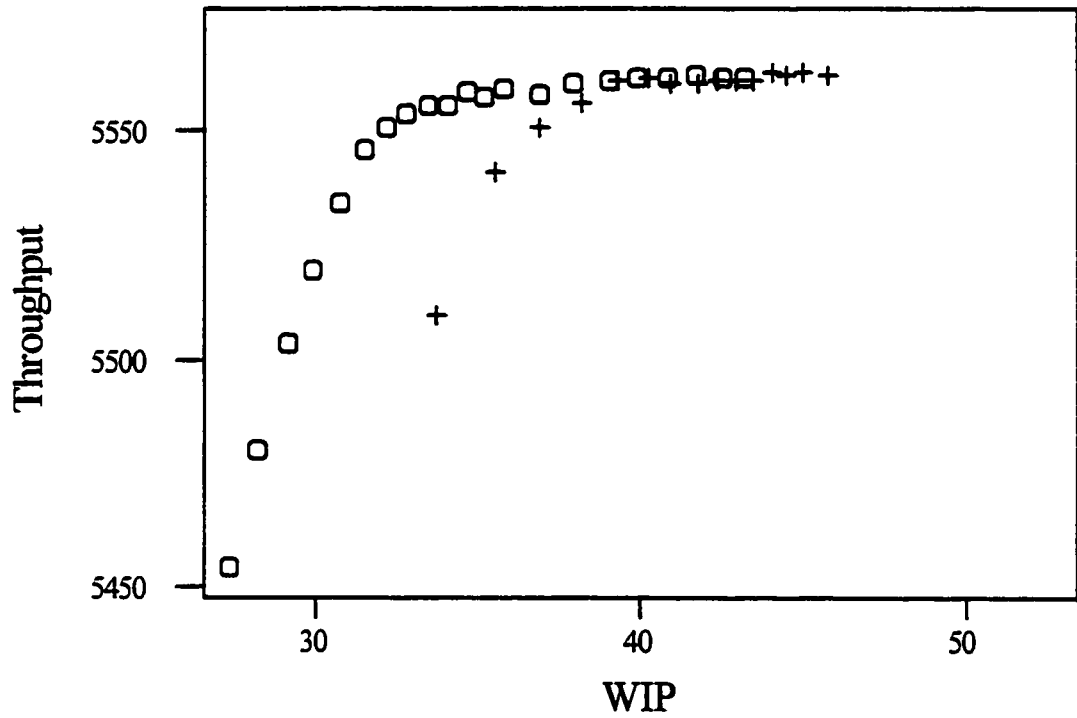
Flowshop; operating curves; 112



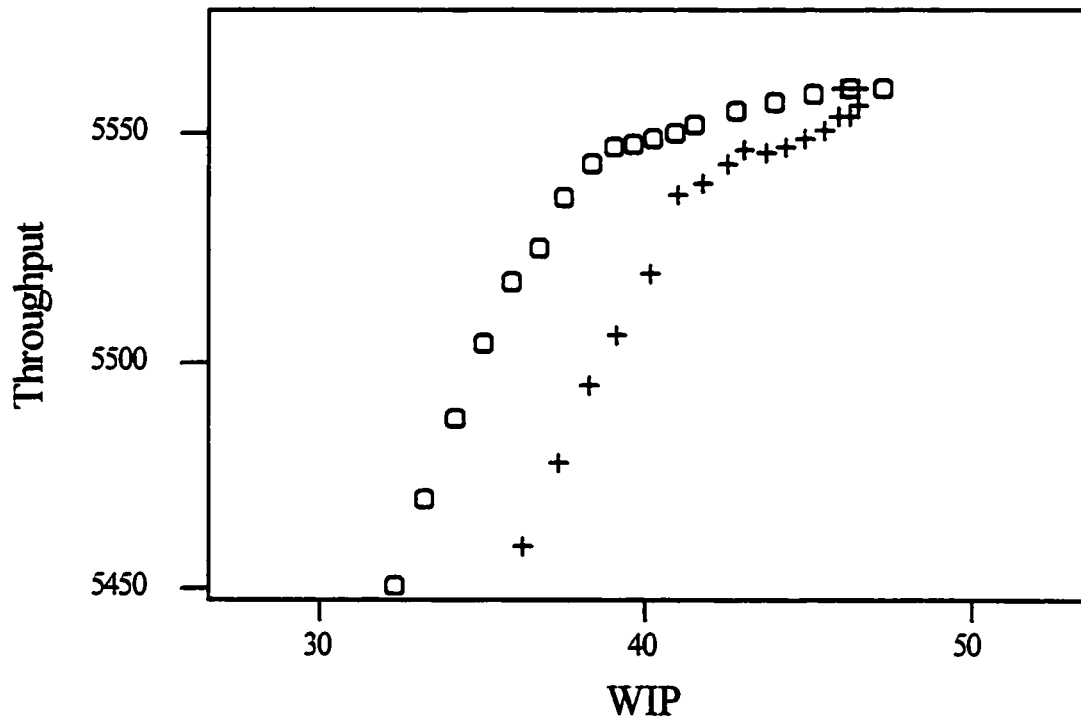
Flowshop; operating curves; 121



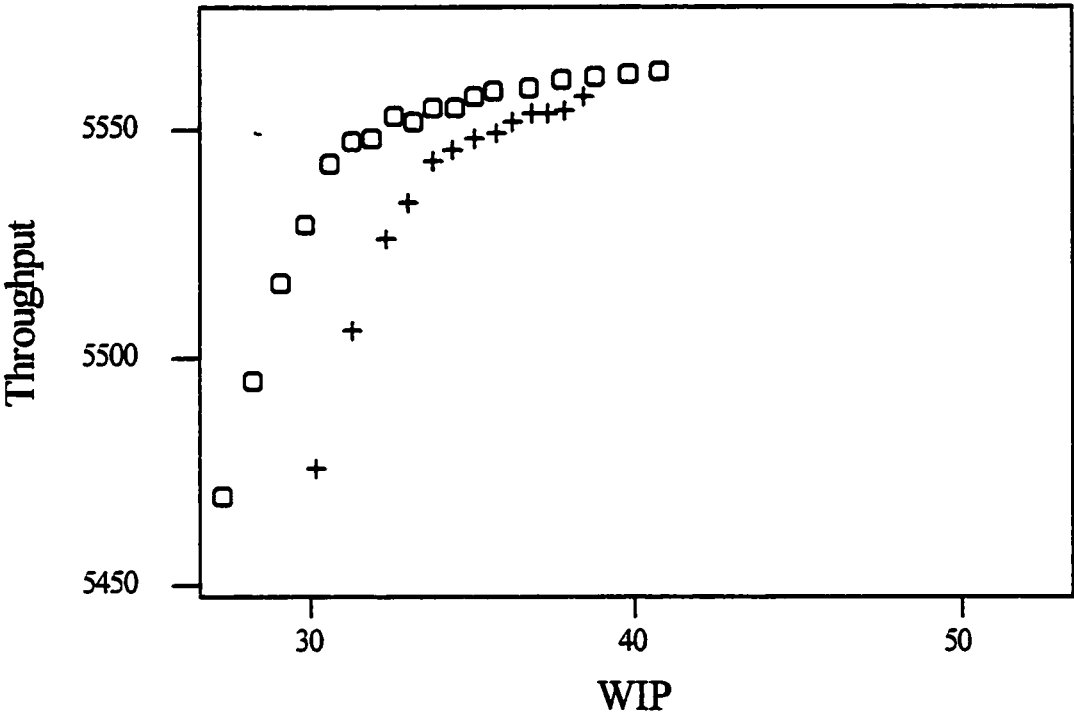
Flowshop; operating curves; 122



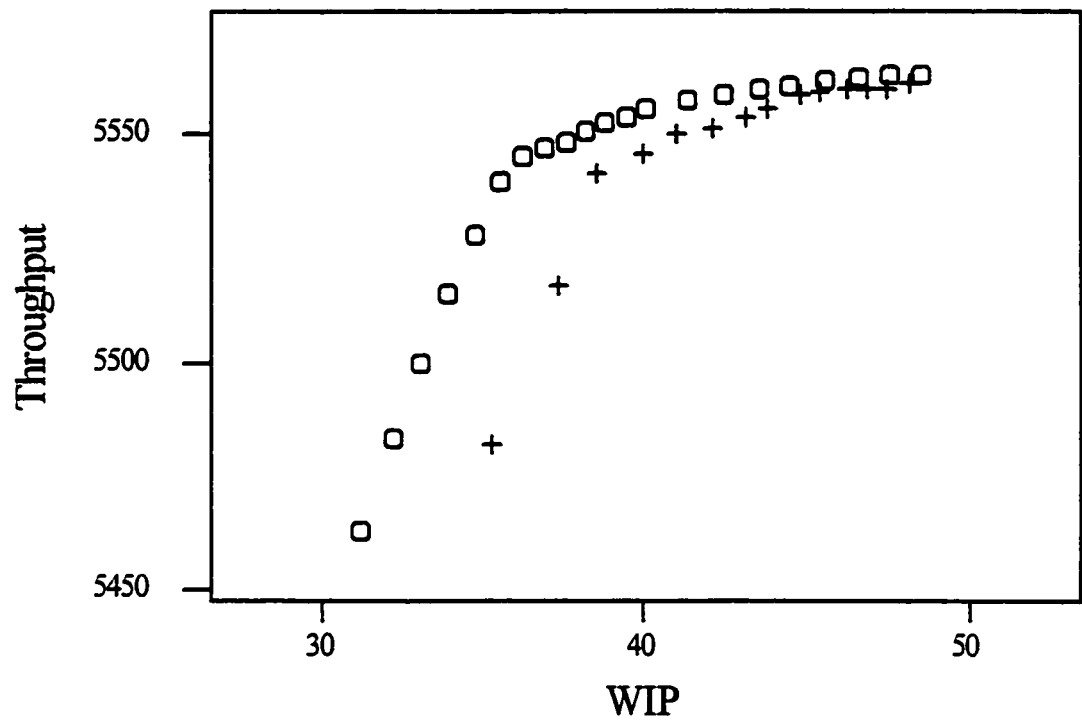
Flowshop; operating curves; 211



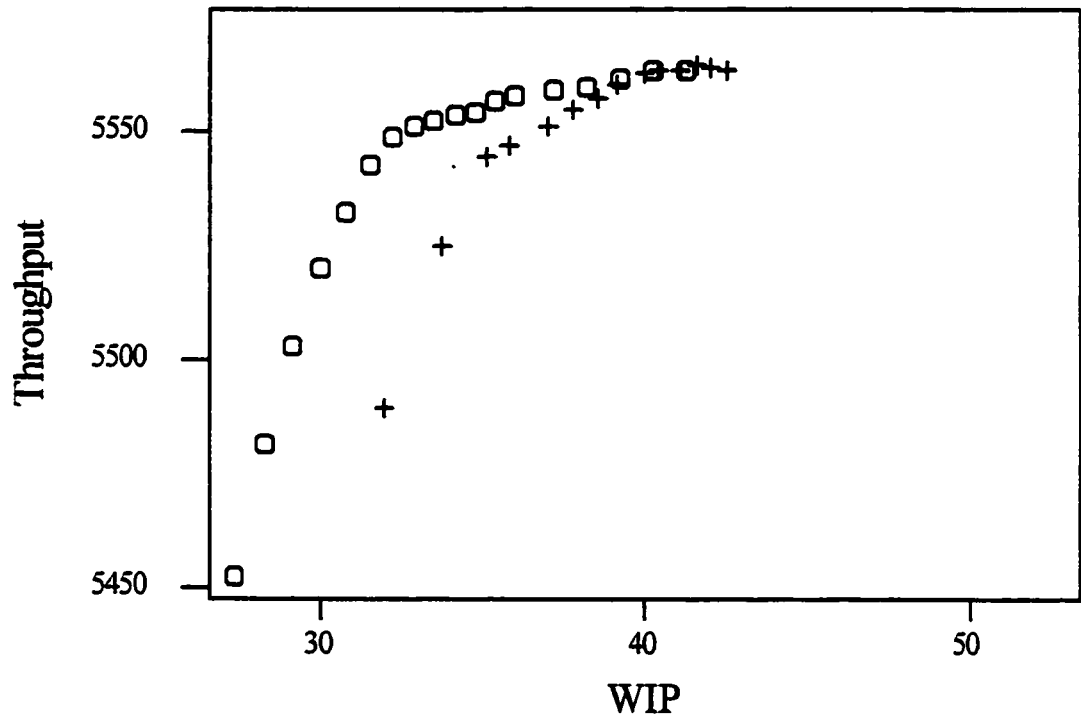
Flowshop; operating curves; 212



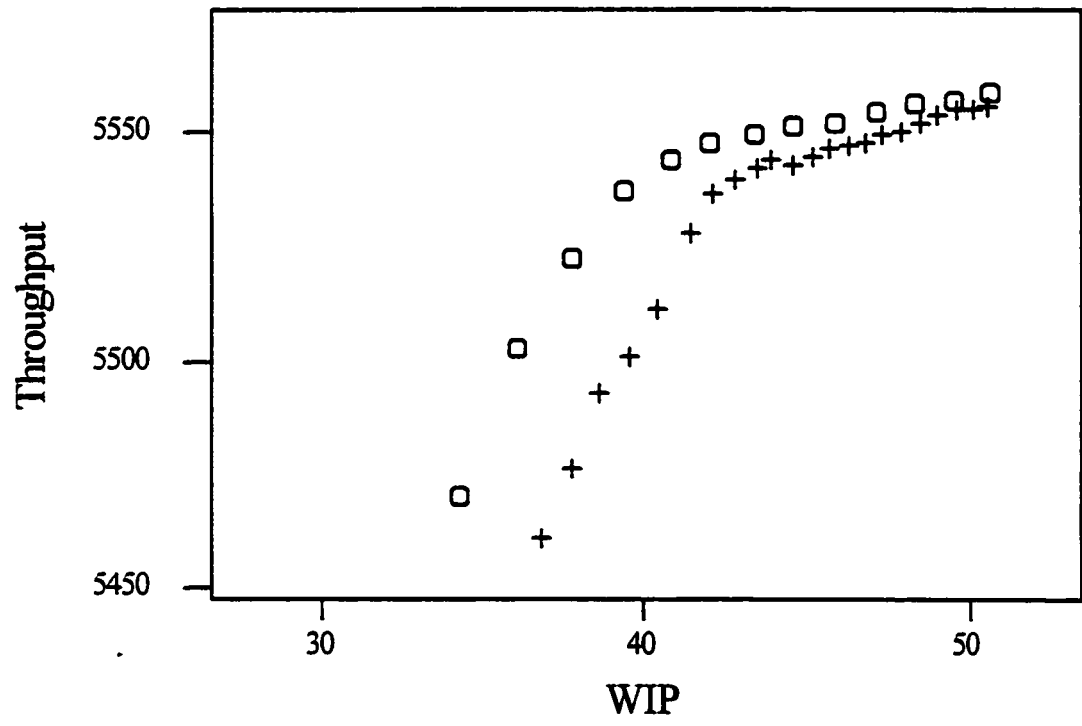
Flowshop; operating curves; 221



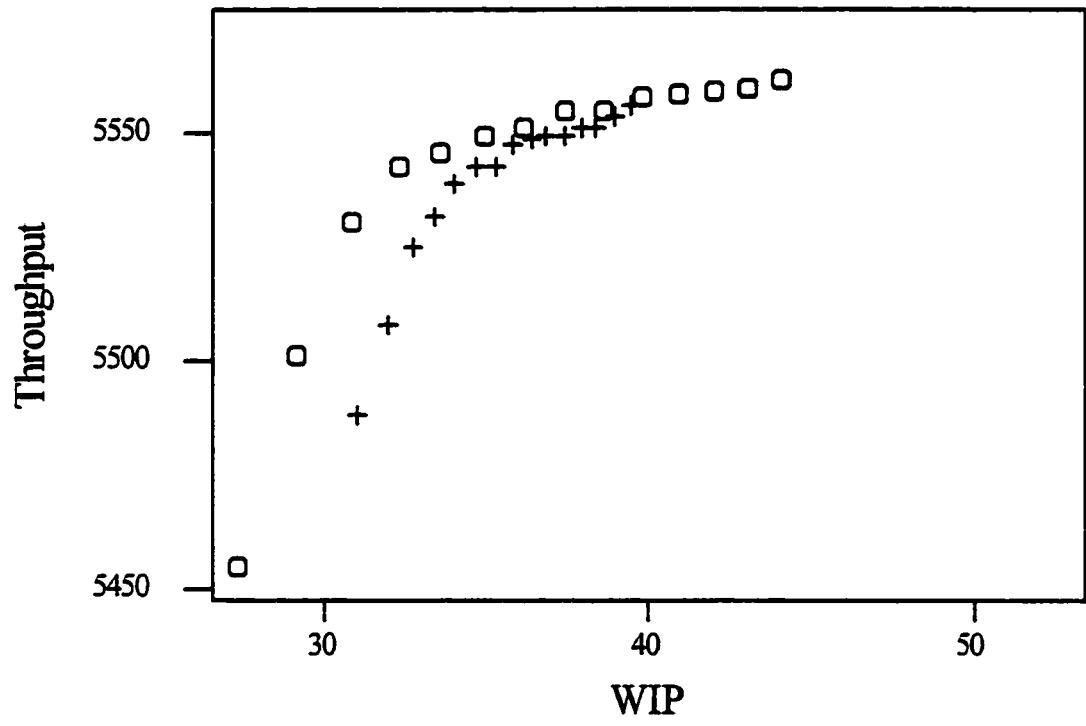
Flowshop; operating curves; 222



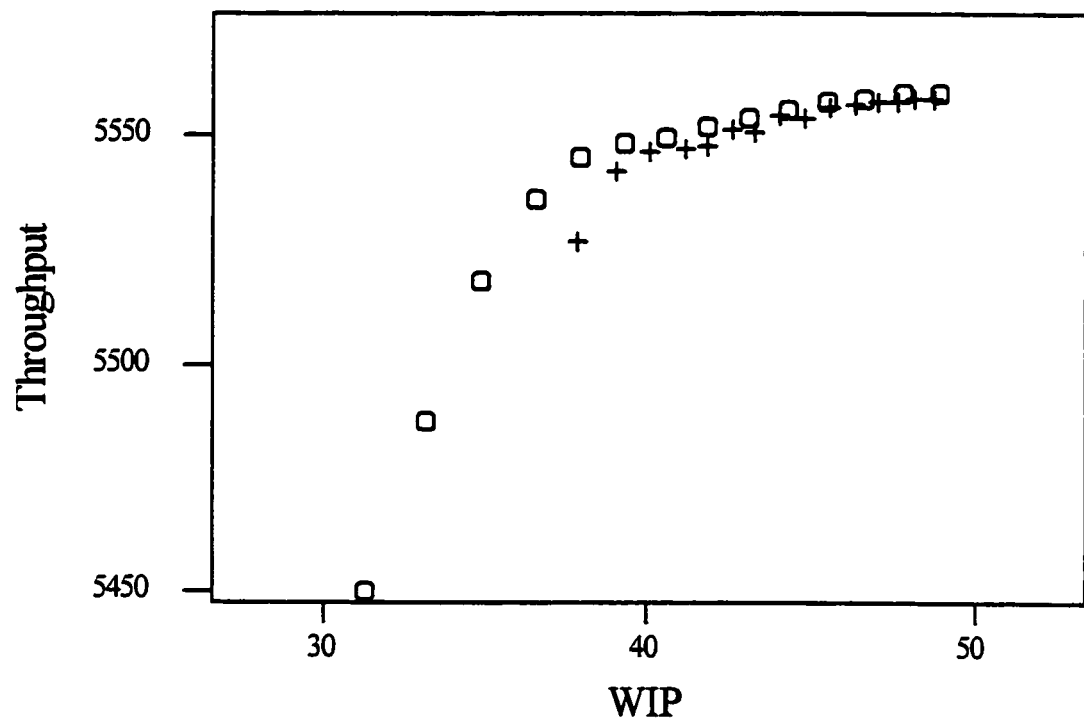
Flowshop; operating curves; 311



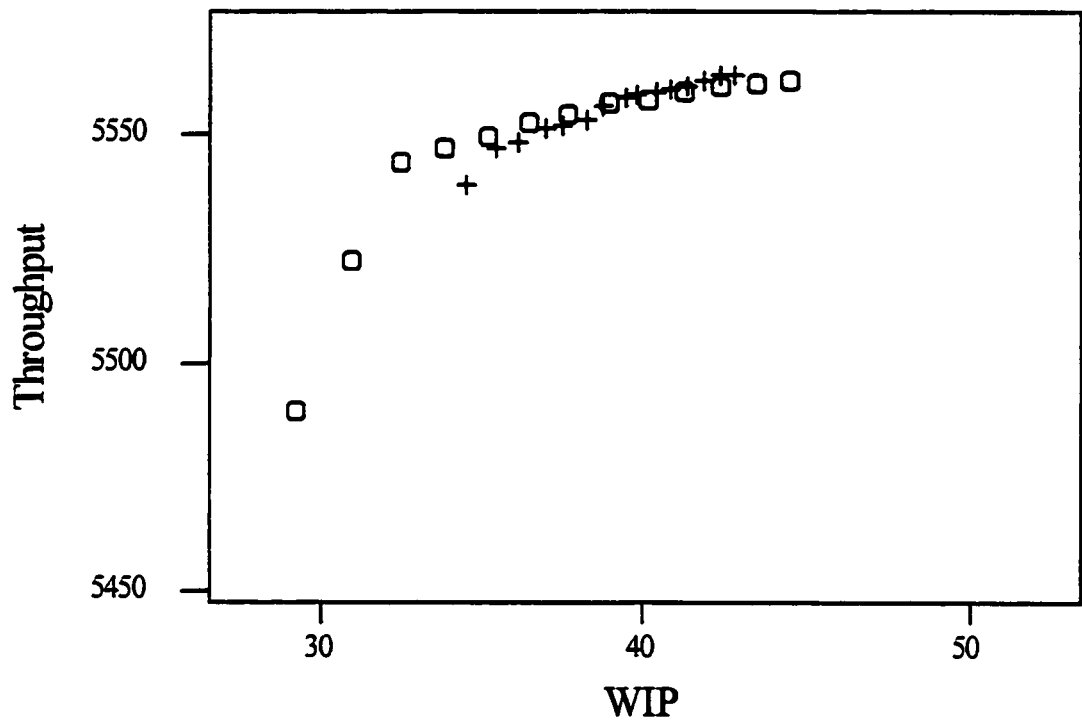
Flowshop; operating curves; 312



Flowshop; operating curves; 321

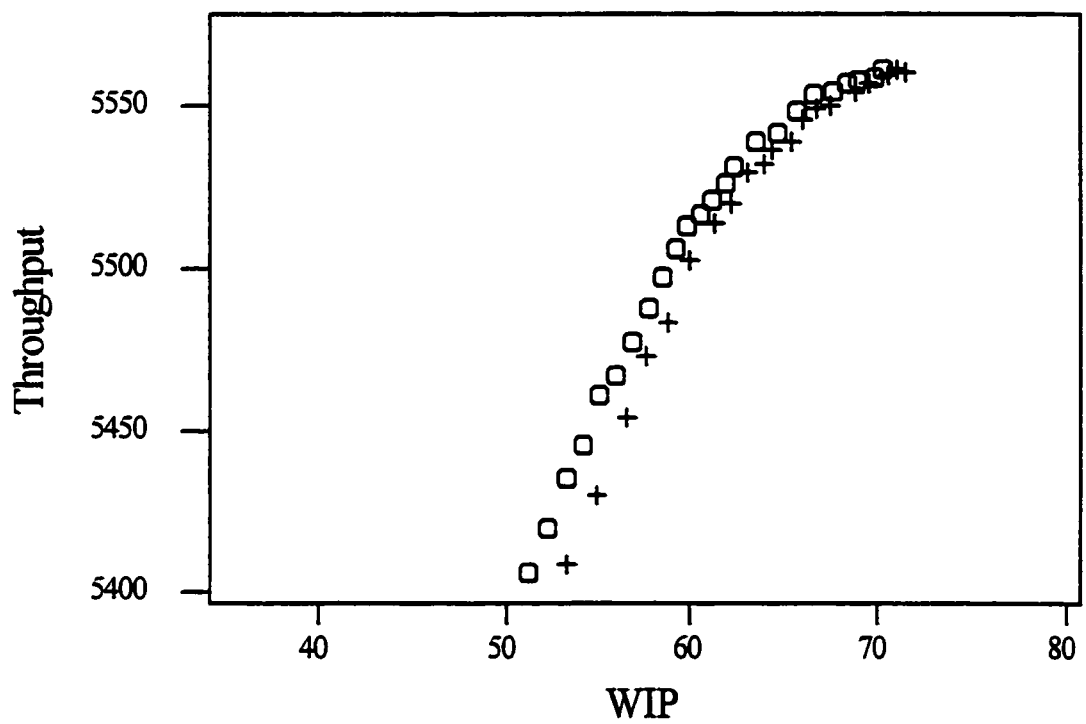


Flowshop; operating curves; 322

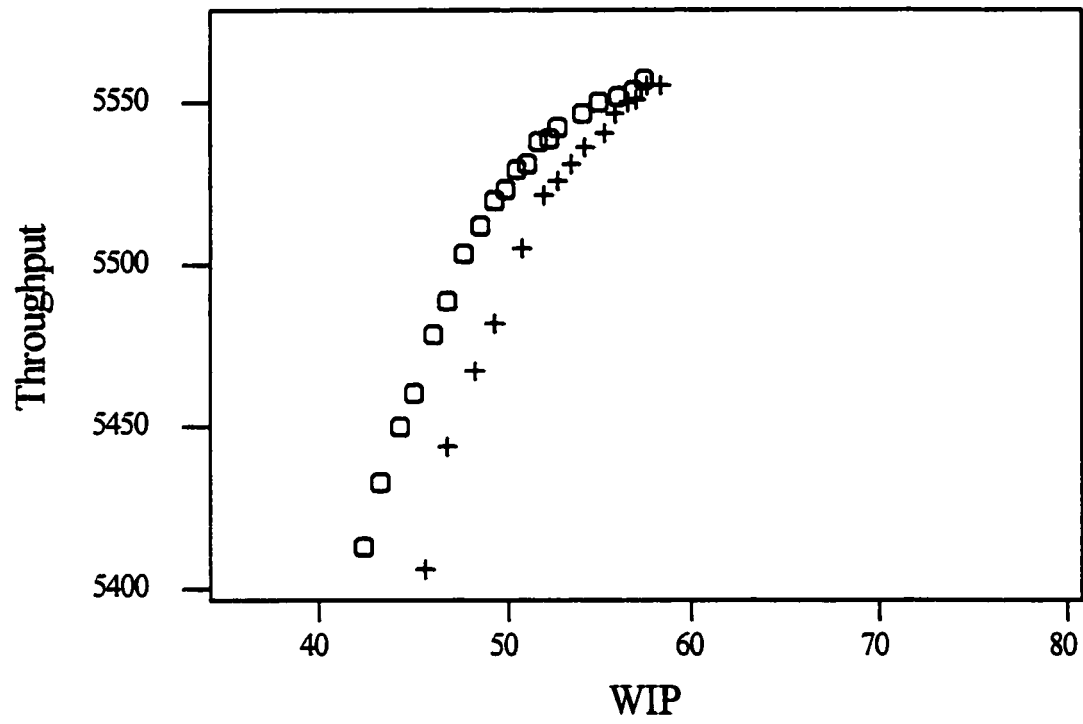


Appendix 7. Operating curves for the jobshop

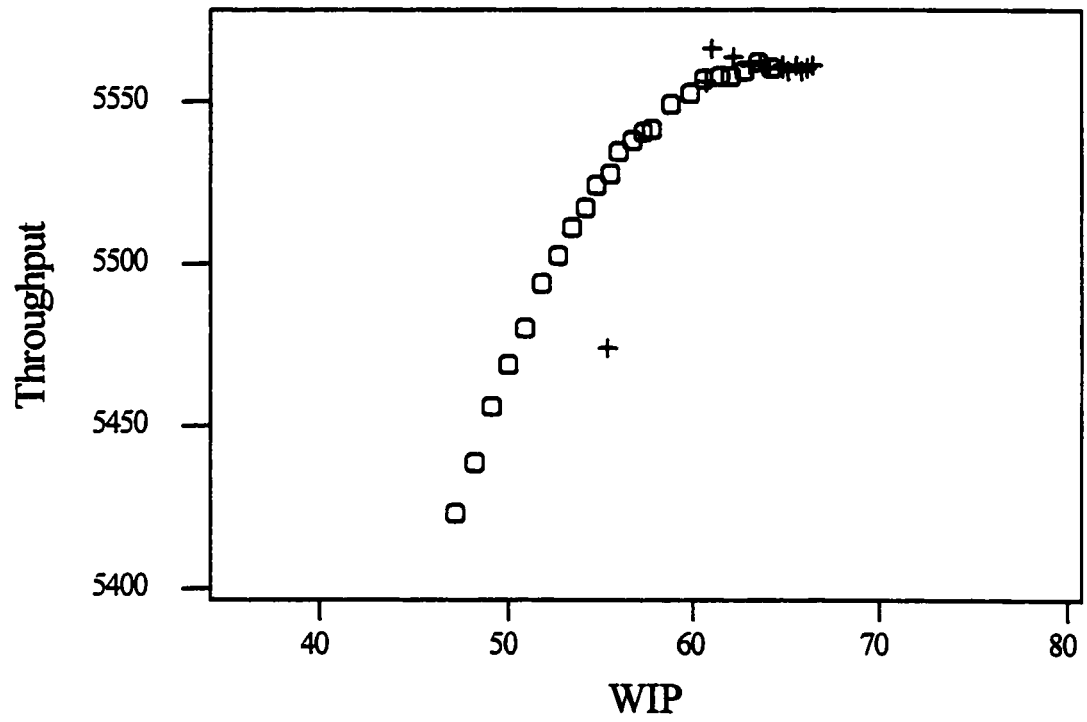
Jobshop; operating curves; 1 1 1



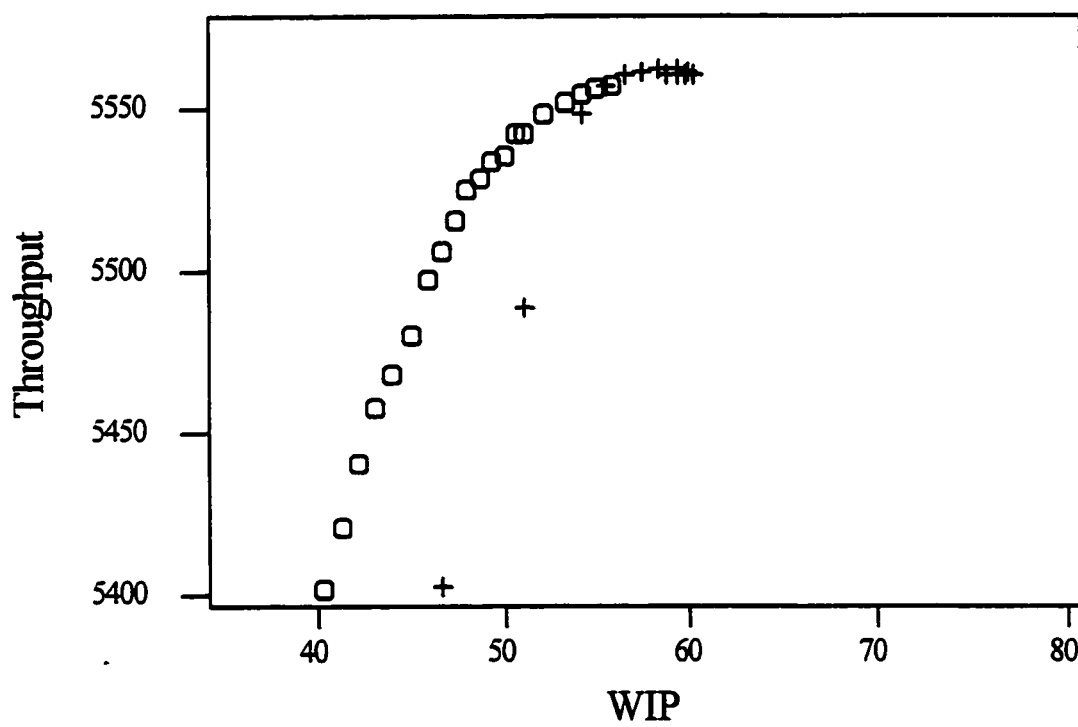
Jobshop; operating curves; 112



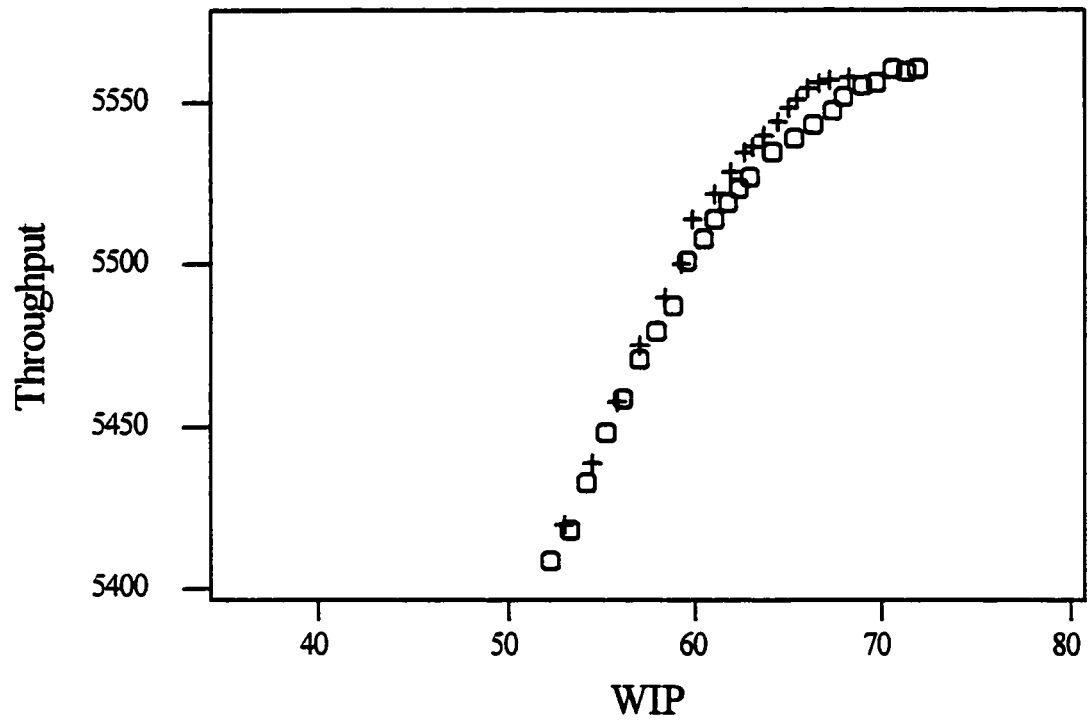
Jobshop; operating curves; 121



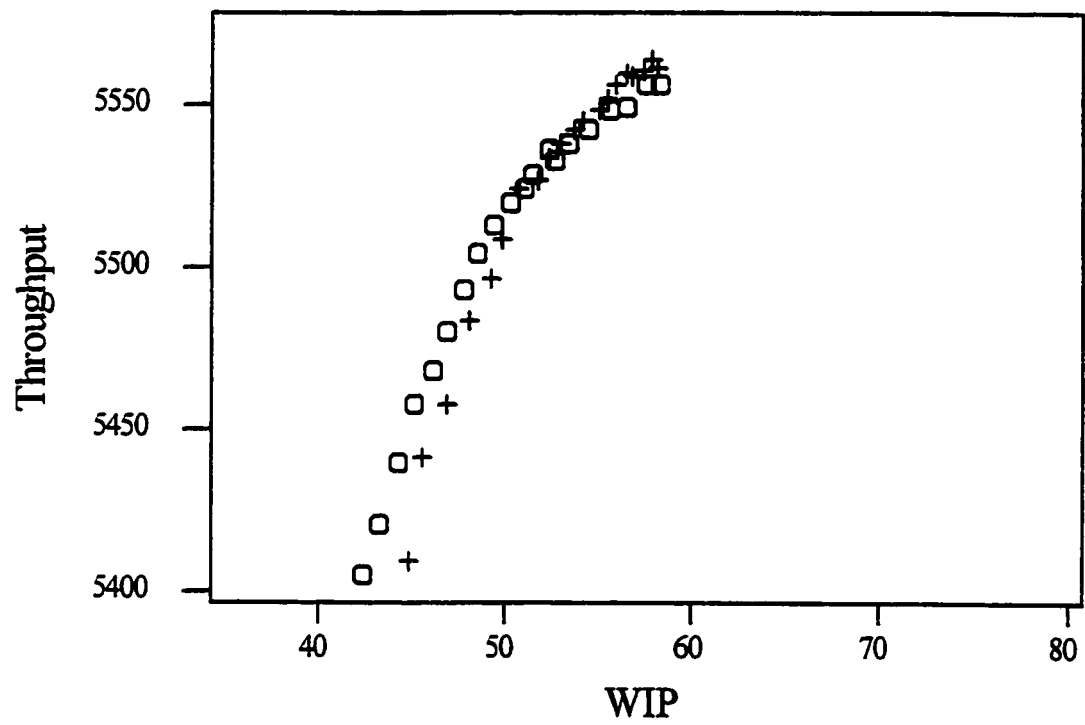
Jobshop; operating curves; 122



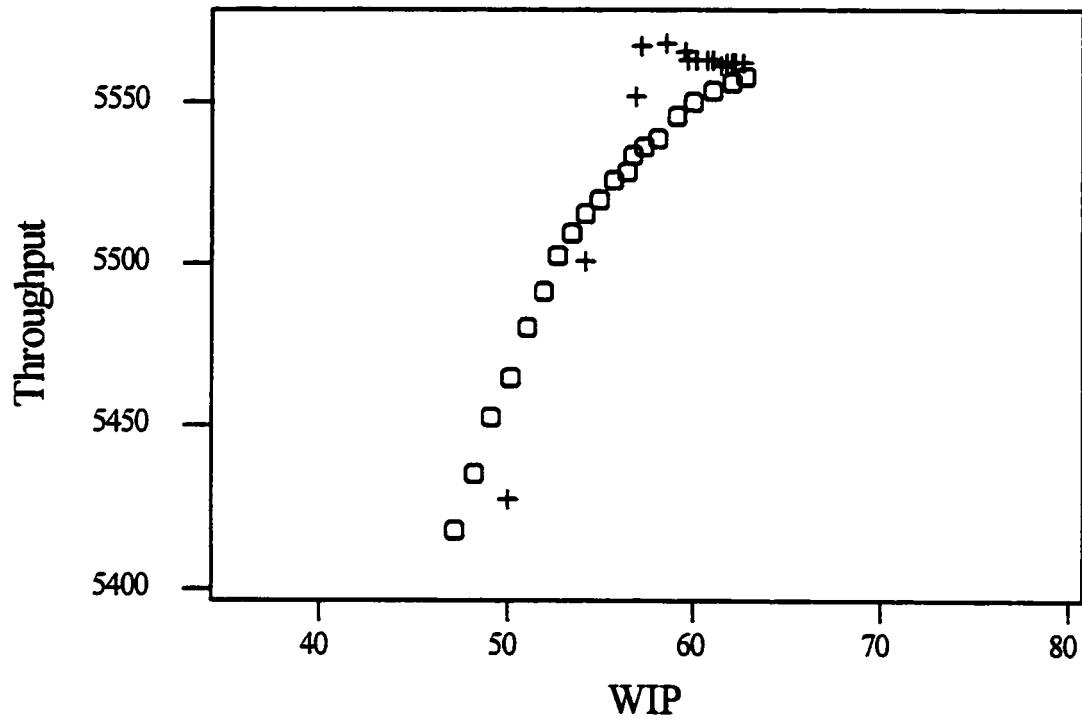
Jobshop; operating curves; 211



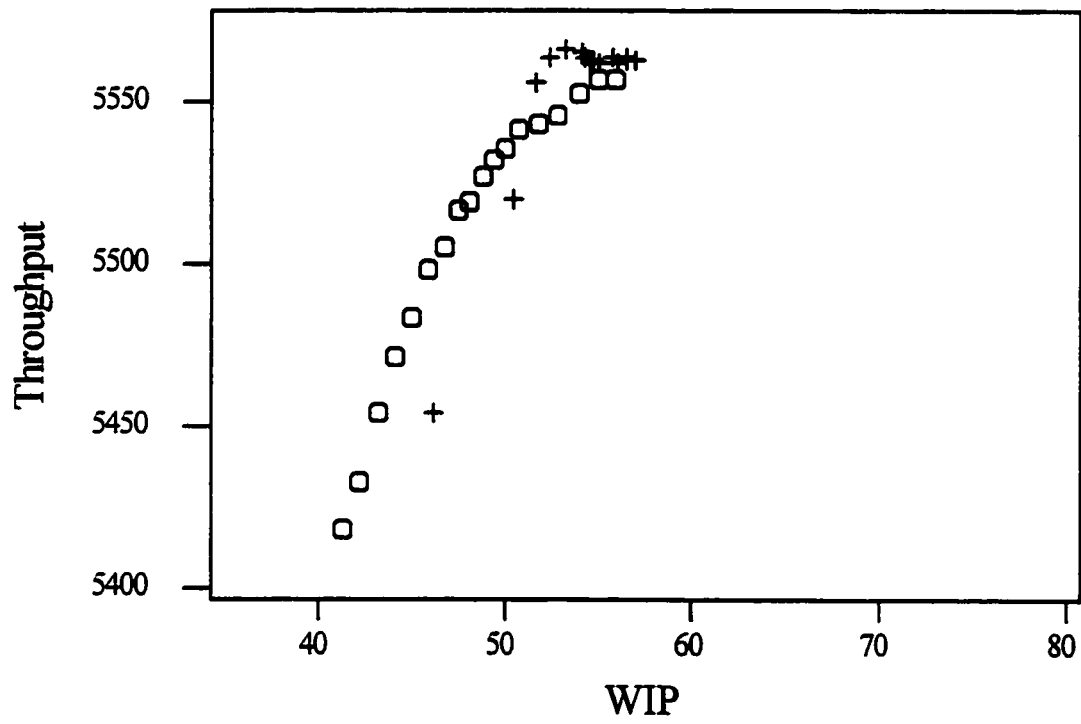
Jobshop; operating curves; 212



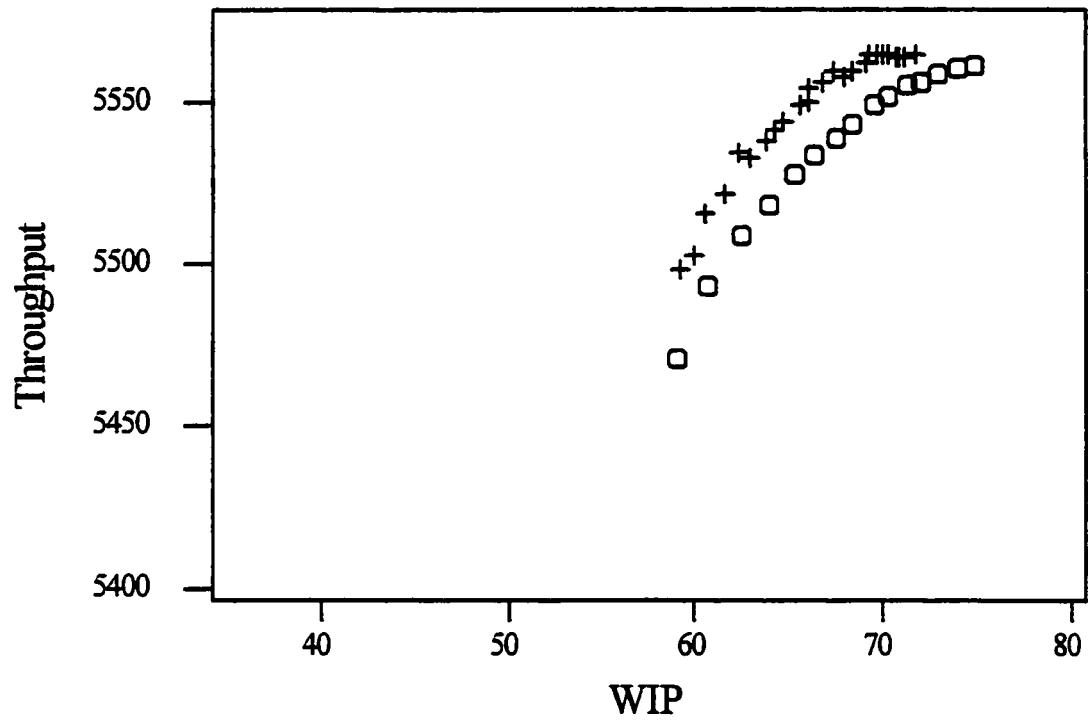
Jobshop; operating curves; 221



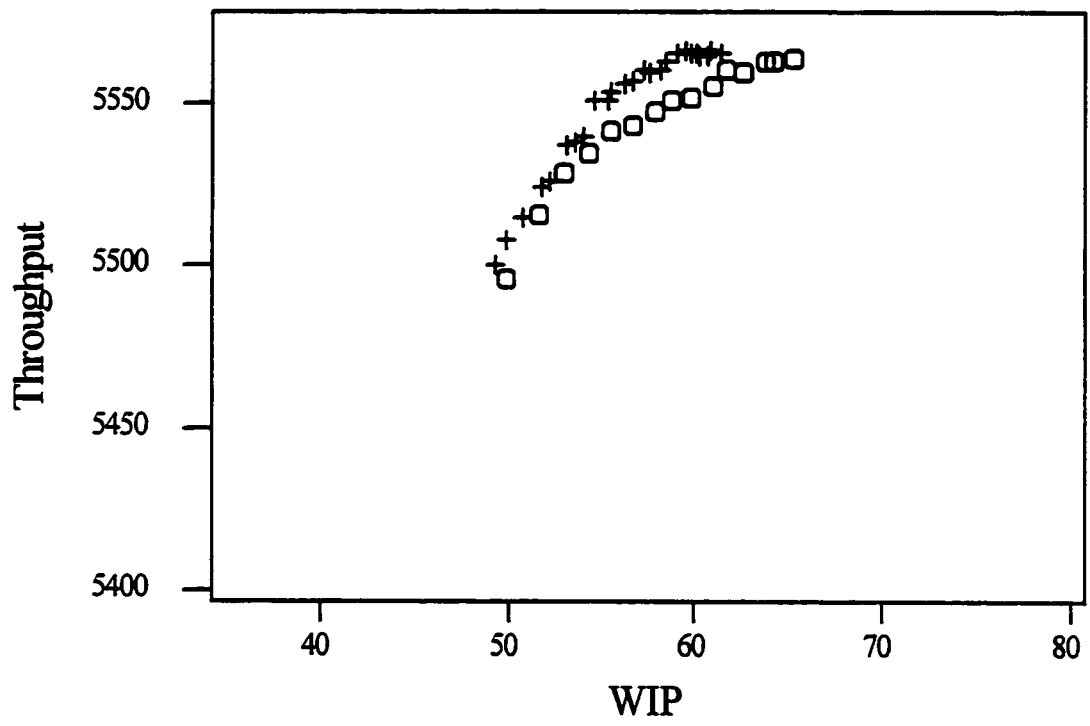
Jobshop; operating curves; 222



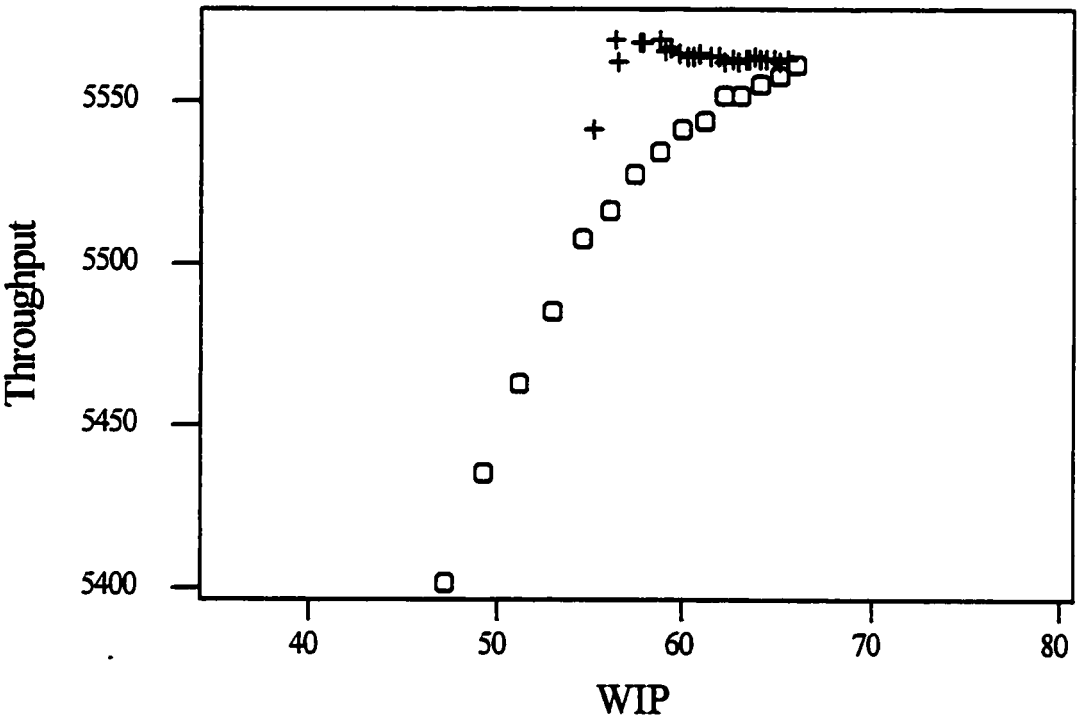
Jobshop; operating curves; 311



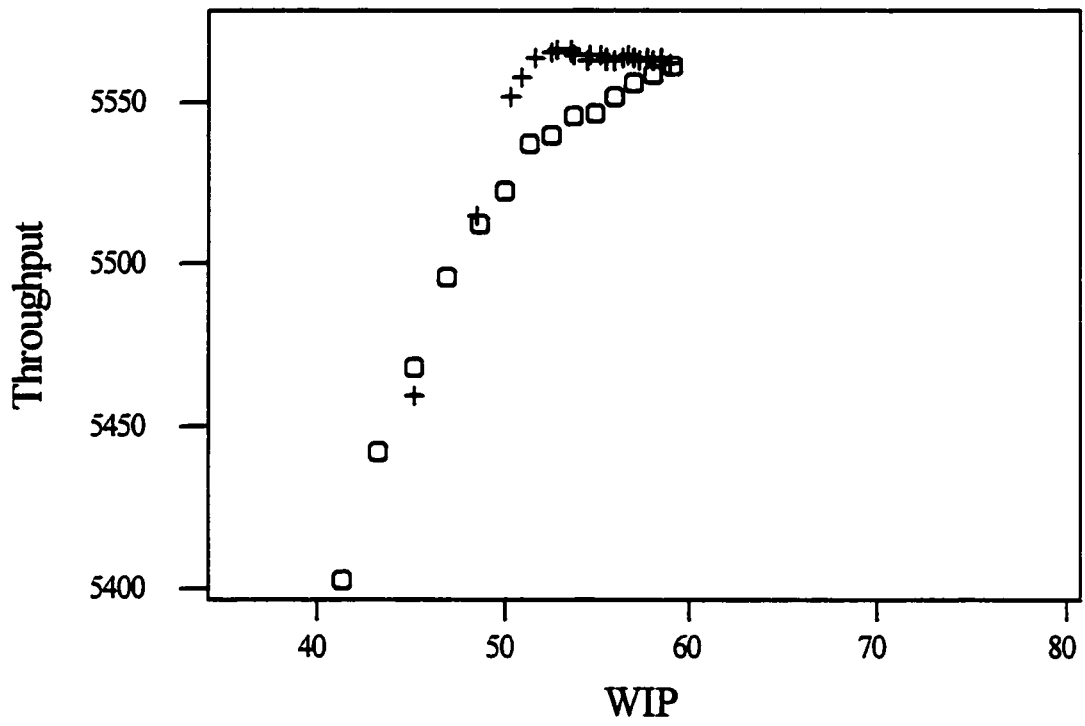
Jobshop; operating curves; 312

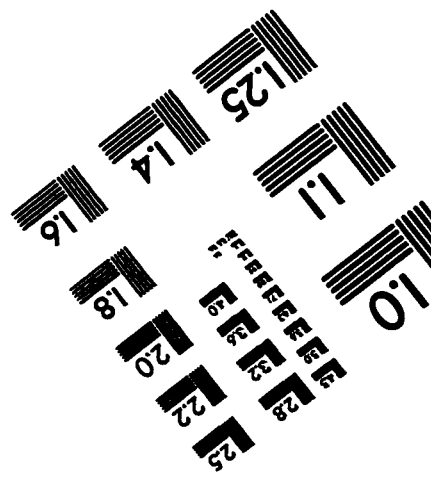
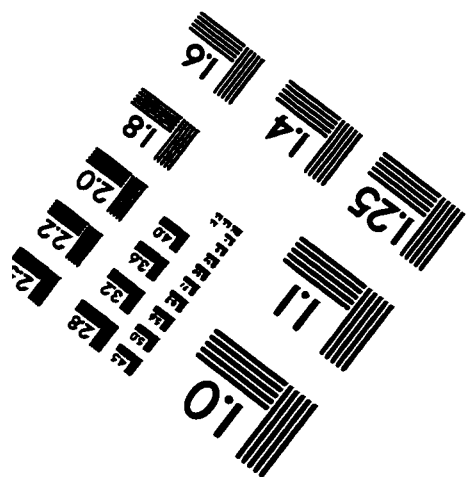
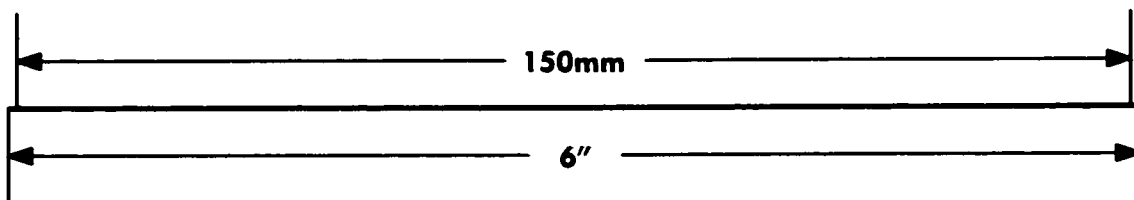
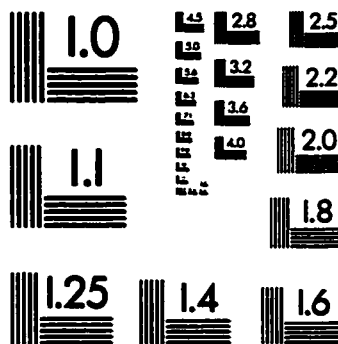


Jobshop; operating curves; 321



Jobshop; operating curves; 322





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