"Anticipatory Batch Insertion"
To Mitigate Perceived Processing Risk

By

Smitha Elzebeth Varghese

A thesis
presented to the University of Waterloo
in fulfillment of the
thesis requirement for the degree of
Master of Applied Science
in
Management Sciences

Waterloo, Ontario, Canada, 2004

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Abstract

The literature reviewed on lot-sizing models with random yields is limited to certain random occurrences such as day to day administrative errors, minor machine repairs and random supply due to faulty delivery of parts. In reality however, the manufacturing industry faces other risks that are non random in nature. One example would be yield discrepancies caused by non random triggers such as a change in the production process, product or material. Yield uncertainties of these types are temporary in nature and usually pertain until the system stabilizes. One way of reducing the implications of such events is to have additional batches processed earlier in the production that can absorb the risk associated with the event. In this thesis, this particular approach is referred to as the *anticipatory batch insertion* to mitigate perceived risk.

This thesis presents an exploratory study to analyze the performance of batch insertion under various scenarios. The scenarios are determined by sensitivity of products, schedule characteristics and magnitude of risks associated with causal triggers such as a process change. The results indicate that the highest return from batch insertion can be expected when there are slightly loose production schedules, high volumes of sensitive products are produced, there are high costs associated with the risks, and the risks can be predicted with some degree of certainty.

Keywords: Disruption, Batch Insertion, Schedule Hardness, Weighted Tardiness.

Acknowledgements

The presentation of this thesis is possible due to the constant help and support provided by my supervisor Kenneth McKay. I would like to thank my readers: Drs. Samir Elhedhli and Elizabeth Jewkes for their valuable comments. I want to thank my friends Kimberly Zheng and Mike Bobinski for the friendship and support they have offered during the course of my graduate career. I would also like to thank Kimberly Zheng and Robin George for proof reading this thesis. Finally, I want to express my sincere gratitude to Dr. Frank Safayeni and Lynne Wight for making it possible for me to complete the degree requirements.

Dedication

This thesis is dedicated to my parents and my husband who have been a constant support in all my academic endeavors.

TABLE OF CONTENTS

INTRODUCTION 1

MOTIVATION 4

LITERATURE REVIEW 13

3.1 Lot-Sizing When Yield Is Deterministic 14

3.2 Lot-sizing When Yield Is Random 17

3.3 Modeling and Analysis Methodology 22

3.4 Summary 27

CONCEPTUAL DEVELOPMENT 29

4.1 Problem Scope, Simplifying Assumptions 29

4.2 Brief Overview Of The Single-Machine Scheduling Structure 32

4.3 Elements Of The Scheduling Formulation 34

4.4 Conceptual Framework 41

4.5 Research Questions and Propositions 43

4.6 Summary 47

EXPERIMENTAL DESIGN 48

5.1 EXPERIMENTAL STRUCTURE 48

5.2 Experimentation Design 50

5.3 Verification and Validation. 58

5.4 Summary 59

EXPERIMENTATION RESULTS 60

6.1 Results under different experimental cases 62

6.2 Schedule Hardness 63

6.3 Sensitivity of Products 66

6.4 Magnitude of Risk 67

6.5 Summary 69

ANALYSIS AND DISCUSSION 70

7.1 Experimental Cases 70

7.2 Schedule Hardness..72

7.3 Sensitivity of Products...75

7.4 Magnitude of Risk 77

7.5 Summary 79

EXPERIMENTAL ROBUSTNESS 80

8.1 Setup Costs..80

8.2 Dollar Per Scrap 83

8.3 Cost Per Piece 84

8.4 Dollar per Time 86

8.4 Summary 87

IMPLICATIONS AND LIMITATIONS 89

9.1 Implications...89

9.2 Limitations 91

FUTURE RESEARCH AND CONCLUSIONS 92

10.1 Future Research..92

10.2 Conclusion..93

REFERENCES 96

APPENDICES 101

APPENDIX A: EXPERIMENT SCENARIOS 101

APPENDIX B: RESULTS FOR VERIFICATION OF LOGIC 103

APPENDIX C: MATLAB CODE 105

LIST OF TABLES

TABLE 4.1 NOMINAL JOB-SET: NO CAUSAL TRIGGERS....36
TABLE 4.2 ANTICIPATORY BATCH INSERTION CONCEPT- PREDICTION OF VARIANCES IN COST....40
TABLE 5.1 SUMMARY OF RESEARCH QUESTIONS AND PROPOSITIONS 52
TABLE 5.2 SCHEDULE HARDNESS CRITERIA 55
TABLE 6.1 PERFORMANCE MEASURES-EXPERIMENTAL CASES....63
TABLE 6.2 PERFORMANCE MEASURES- SCHEDULE HARDNESS (NO DISRUPTION-NO INSERTION)....64
TABLE 6.3 PERFORMANCE MEASURES- SCHEDULE HARDNESS (DISRUPTION-NO INSERTION) 65
TABLE 6.4 PERFORMANCE MEASURES- SCHEDULE HARDNESS (DISRUPTION- INSERTION) 65
TABLE 6.5 PERFORMANCE MEASURES- SCHEDULE HARDNESS (NO DISRUPTION--INSERTION) 65
TABLE 6.6 PERFORMANCE MEASURES- PRODUCT SENSITIVITY (NO DISRUPTION-NO INSERTION)....66
TABLE 6.7 PERFORMANCE MEASURES-PRODUCT SENSITIVITY (DISRUPTION-NO INSERTION)....66
TABLE 6.8 PERFORMANCE MEASURES-PRODUCT SENSITIVITY (DISRUPTION-INSERTION) 67
TABLE 6.9 PERFORMANCE MEASURES- PRODUCT SENSITIVITY (NO DISRUPTION- INSERTION)....67
TABLE 6.10 PERFORMANCE MEASURES- MAGNITUDES OF RISK (NO DISRUPTION-NO INSERTION)....68
TABLE 6.11 PERFORMANCE MEASURES- MAGNITUDES OF RISK (DISRUPTION-NO INSERTION)....68
TABLE 6.12 PERFORMANCE MEASURES- MAGNITUDES OF RISK (DISRUPTION- INSERTION) 68
TABLE 6.13 PERFORMANCE MEASURES- MAGNITUDES OF RISK (NO DISRUPTION-INSERTION)....69
TABLE 7.1 PERCENTAGE INCREASE IN COSTS AND WEIGHTED TARDINESS VALUES....71
TABLE 7.2 SCHEDULE HARDNESS-WEIGHTED TARDINESS....73
TABLE 7.3 SENSITIVITY OF PRODUCTS-IMPROVEMENT IN PERFORMANCE (TWO PRODUCTS)....75
TABLE 7.4 SENSITIVITY OF PRODUCTS-PERFORMANCE MEASURES (FIVE PRODUCTS) 76
TABLE 7.5 MAGNITUDES OF RISK-PERFORMANCE MEASURES....77
TABLE 8.1 ADDITIONAL SETUP COST- COST VALUES 81
TABLE 8.2 ADDITIONAL SETUP COSTS- PERFORMANCE IMPROVEMENT 81
TABLE 8.3 DOLLARPER SCRAP- COST IMPROVEMENTS 83
TABLE 8.4 COST PER PIECE- COST IMPROVEMENTS 85
TABLE 8.5 DOLLAR PER TIME- COST IMPROVEMENTS 86

LIST OF FIGURES

FIGURE 4.1 CONCEPTUAL MODEL..42
FIGURE 5.1 STRUCTURAL COMPONENTS..50
FIGURE 7.1 SCHEDULE HARDNESS VS PERFORMANCE IMPROVEMENT..74
FIGURE 7.2 A & B SENSITIVE PRODUCTS VS PERFORMANCE IMPROVEMENTS...76
FIGURE 7.3 A & B MAGNITUDE OF RISK VS PERFORMANCE IMPROVEMENT..78
FIGURE 8.1 ADDITIONAL SETUP COSTS VS COST IMPROVEMENTS..82
FIGURE 8.2 DOLLAR PER SCRAP VS IMPROVEMENT IN COST..84
FIGURE 8.3 COST PER PIECE VS COST IMPROVEMENTS..86
FIGURE 8.4 DOLLAR PER TIME VS COST IMPROVEMENTS..87

CHAPTER 1

INTRODUCTION

A substantial body of research has focused on lot-sizing decisions with random yields (Yano and Lee, 1995). This research has addressed various causes of random yield, including imperfect production processes, unexpected machine breakdowns, uncertain repair durations, and rework of defective units. These are all stochastic situations and typical strategies in the research call for increasing quantities to deal with scrap, or establishing suitable safety-stock levels. In the literature, non-random or predictable causes of yield variance are not addressed and there appear to be no specific production control strategies for decreasing the yield variance. In this thesis, we will address non-random sources of yield variance associated with deterministic triggers such as changes in product composition, processes, personnel, and material. Specifically, we will introduce and explore a strategy for addressing and reducing the yield variance associated with such situations.

Introduction of a new product, process, personnel, or material can be a significant source for yield variance (e.g., McKay, 1992; Grosfeld-Nir and Gerchak, 2004). For example, the substitute material from a new supplier might not react in exactly the same way as the old material or the documentation might be out of date for a job that is run irregularly, or there are new operators on the machine. All of these changes can result in batches of work being scrapped. In a perfect world, this would not be true but in a real factory, any change in the status quo or normal situation can result in manufacturing problems. The risk associated with such problems will pertain until the system stabilizes and is requalified. In this thesis, the risk associated refers to the scrapping of end items or final products.

There can be a number of strategies used to address random and non-random yield variance. One class of strategies for random yield variance is largely reactive; this class involves the creation of safety stock or the creation of additional work orders once the yield loss hits a certain level. Another class of strategies associated with random yield variance is somewhat anticipatory as batch sizes are artificially increased by the predicted yield loss. These three strategies have been largely developed for the situations where the loss is a relatively small percentage of the batch size (e.g., 5-15%). In the case of a significant non-random loss, a system with no feed-forward control can simply react to the loss through the creation of a replacement batch. However, it is possible to contemplate feed-forward strategies to minimize certain non-random losses.

One such strategy has been observed in empirical work performed by McKay (1992). In this strategy small *extra* batches are created by the scheduler and run earlier in the production schedule - to absorb the risk implications associated with a change in production environment (process, product or material), thus causing fewer items to be scrapped. We call this particular approach, ***anticipatory batch insertion to mitigate risk***. If the risk does not materialize, the strategy is equivalent to a batch-splitting; if the risk materializes and high scrap rates occur, the extra batch represents additional material and resource allocations. The performance and tradeoffs of this approach are analytically studied using a simulation model with respect to cost and tardiness factors. We also analyze the sensitivity of the performance of this approach to the risk and production characteristics like due dates, sensitivity of the products to disruptions caused by causal triggers such as a process change, and the magnitudes of the loss associated with the disruptions. Further, we test the robustness of the model by varying the various experimental settings.

The problem characteristics and the different ways of coping with such unusual events by the industry are detailed in Chapter 2. A general literature review of lot-sizing models is provided in Chapter 3. Chapter 4 describes the problem characteristics and develops a model to explore the problem. Chapter 5 details the experimental design. Chapter 6 tabulates the results from the experimentation according to the different experimental scenarios and chapter 7 discusses and analyzes the results obtained from the experimentation. Chapter 8 discusses the robustness of the experimentation. Chapters 9 and 10 focus on implications, limitations, future research, and conclusions.

CHAPTER 2

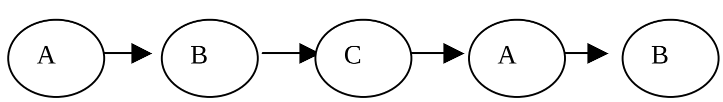
MOTIVATION

As shown in the literature review, the majority of random yield models studied in the literature appear to deal with imperfect production processes or variable capacities. The modeling methods increase either the quantity or the number of batches to reduce the implications of such events (Anily et al., 2002; Grosfeld-Nir and Gerchak, 2004).

Empirical research suggests that production processes can incur losses of high magnitude, which are commonly caused by unusual but predictable production activities (McKay, 1992; Grosfel-Nir and Gerchak, 2004). As noted in McKay (1992), these kinds of events are typically not addressed by the traditional planning processes. When they occur, there are significant costs and losses that are unanticipated, and the loss in productivity further destabilizes the manufacturing situations. For example, electronic manufacturers can be highly susceptible to such risks, as many of the parts are easily damaged and are expensive. In this type of situation, the unnecessary scrapping of large quantities should be avoided, if possible. For instance, at one point, an Intel P4-3.2CGHz CPU cost upwards of $900 (retail) and it would be expensive to scrap a board containing such a chip. Even if the work can be reclaimed, there is always a chance for additional damage to the parts and the cost of reclaiming. To illustrate some of the unusual incidents faced by a manufacturing plant, we give several examples from a field study conducted by McKay (1992). The field study was conducted at a state-of-the-art printed circuit board manufacturer who was using surface mounted technology. In one example, a process change introduced by industrial engineering worked fine for most parts but affected a job that was irregularly run causing the final products to be scrapped. In another example, the supplier of a certain material was different from the last time the product was run; although the material was supposedly the same, it had different processing characteristics that resulted in high scrap rates on the first batch. In yet another example, machines had been upgraded since the last batch had been run of a specific part – machine settings changed, additional features added - changes that were not thoroughly understood by the operators and engineers with respect to the infrequently run part. The batch was scrapped. These types of problems are associated with close tolerance work with high demands of accuracy and in situations where the processing at one step cannot be checked until later in the processing flow - after the batch has completed one or more operations.

A scheduler can implement different approaches to deal with the different types of situations mentioned above. Some approaches are implemented after the defective units are identified (Reactive) while others can be implemented in anticipation of the risk involved (Proactive).

Consider the following schedule of five jobs. These five jobs can be considered to be a *job-set*. One job-set satisfies the demand for a certain time period.



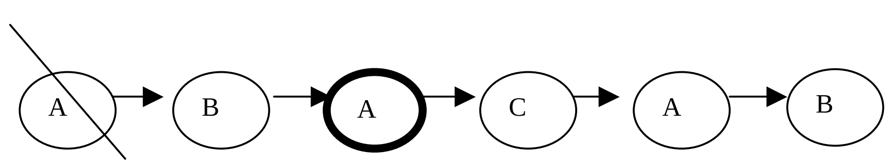
Part A is produced in the first job, followed by jobs producing parts B, C, A, and B. Multiple orders for a part can appear in a single time period for a number of reasons (e.g., racking, oven sizes, etc.) and are used here to illustrate cyclic or repetitive manufacturing.

Suppose that the operators are not skilled on part A, or have forgotten some of the setup instructions, leading to 90% of the output of Job A being scrapped. Let such circumstances that lead to such losses of job outcome be called *causal triggers*.

There are five strategies observed in the literature- approaches used in industry to deal with significant job losses with these types of causal triggers (McKay, 1992; Grosfeld-Nir, 2004; Anily et al., 2002):

1) *Processing another batch*

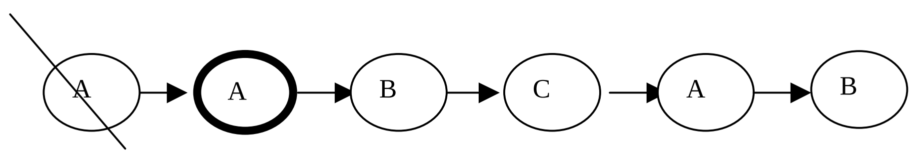
When the disruption is recognized, another job is inserted into the schedule with product type A. In this case, we assume that Job B begins processing before the complete inspection of Job A. This scenario can also result in the case where Job B has to be processed before making up for Job A, due to priority issues. The new schedule will look like the following.



An additional setup cost will be incurred in this case, along with the processing cost of re-producing the 90% that was scrapped. Depending on how tight the schedule is, a portion of the job-set can also end up being late due to the extra setup and production activities. That is, the job becomes tardy.

2) *Immediate processing of another batch*

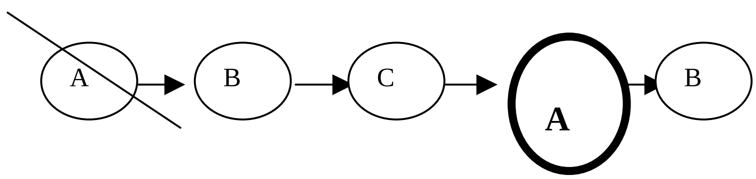
Another batch with Job A is processed immediately after the disruption has occurred. This scenario is different from the above case since the disruption is recognized before the next job is initialized. The new schedule will look like the following.



Depending on the job characteristics or machine characteristics, extra setup costs may or may not be incurred. For example, if the job has to pass through quality control or the machine has to be reset, then extra setup cost will be incurred. However, if the loss is immediately recognized and there is no need for a machine reset, then another job of same type can be processed without incurring 100% of the setup cost. The costs for processing the lost items are incurred in any case. Similar to the above case, there is a chance that the job-set ends up being tardy.

3) *Increasing size of the next batch*

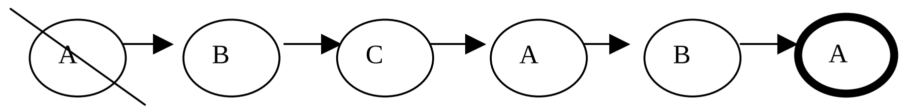
In this case, the size of the next job with the same product type is increased. The amount of increase is equal to the amount lost due to the disruption. For example, if 100 units are processed in every job and 90 units of product A are lost due to the disruption, then the number of units processed in the next job processing product type A would be 190. The schedule remains the same. The only change is the size of the next job with the same product type and the temporary shortfall is accommodated by safety stock. Additional setup costs are not incurred. However, additional tardiness can be introduced due to the extra production time.



This strategy is also used in cases where a safety stock exists. The lost amount is pulled from the safety stock and the outcome of the large batch is used to replenish the safety stock. It is also assumed, that the machine has enough capacity to process the large batch. There might be costs associated with the higher safety stock and there are many practical considerations in manufacturing that prevent the simple doubling of batch sizes.

4) Safety stock

When meeting the due date is a major concern the basic cycle or job-set must be completed, safety stock can be temporarily used to make up for the loss incurred. Safety stock can then be replenished after all the jobs in the job-set are processed (e.g., on a third shift or in a slack period). Again, suppose that we lost 90 units because of the disruption. This amount will be pulled out from the safety stock. Once the job-set is processed and the demand is satisfied, an additional setup is made for product A to replenish the safety stock. The new schedule will be of the form shown below.



It is assumed that safety stock contains enough items to make up for the loss. There will be the expected costs for holding sufficient safety stock. As noted, it is also assumed that the job is setup during slack time and tardiness is not increased for the remainder of the job-set.

5) *Do nothing*

There is always the possibility of doing nothing. If there are more than enough items to satisfy the demand already, nothing is done to recover the 90% lost. This situation is probably very rare, because manufacturers typically do not produce more than what is required due to storage cost, processing cost, raw material cost and other costs involved with production and storage. Nevertheless, this alternative could be applicable to cases where replacement products exist or cases where there is an over supply of products in the market place. For example, where one product is cross-licensed to multiple manufacturers, it is possible acquire a product from the competition and re-label it.

These five approaches are either exclusively or largely reactive in nature. Approaches one through three, and number five are completely reactive in nature since compensation for the scrapped products are made once the disruption has been recognized. Building a safety stock in approach four is somewhat proactive since the safety stock is built in anticipation of the disruption. In other words, the safety stock is built before starting the production process. However, the safety stock is used in a reactive way.

Anticipatory batch insertion to mitigate risk is a proactive approach possibly most suitable for cases where scrapping of an item is expensive (because this approach is designed to reduce the total number of items scrapped). Intuitively, if the due dates are loose, it can be beneficial to make extra setups with small batch sizes earlier in the production, which can absorb the disruption. For example, if a small batch size of ten items is processed in the beginning instead of one hundred, then a 90% loss will result in loosing nine items instead of ninety in the first case. Therefore, the small batch in the beginning reduces the risk implications associated with reducing the amount of items being scrapped and thus preserving expensive raw material used for processing. The rationale is that any problems with processes, settings, instructions, and stabilizations are fixed with the small batch, and will not recur with the second or later batches.

It is not simple enough to say that small batches should always precede larger batches - a heuristic to be applied in every case. Creating extra batches can be costly due to additional setup and production costs, and the possible introduction of added tardiness. Hence, tradeoffs exist in any decision about additional batch insertions with respect to schedule characteristics (schedule hardness) and the production and operating costs. A number of different factors other than setup costs and due dates define this relationship. Some of these factors include magnitude of risk and sensitivity of the product type to the disruption. Magnitude of risk defines the percentage of products lost due to the disruption. It might be more beneficial to incorporate the batch insertion strategy in situation where high magnitude of risk is predicted. It would also be interesting to explore the relationship between the sensitivity of product types and the performance of the strategy. The cost of raw materials is also an obvious contributor to the performance of this batch insertion strategy. If the costs of raw materials are negligent then scrapping of items is not a real problem; certainly not one warranting complex heuristics. On the whole, if the added-value cost of re-producing an item (including cost of time spent in the plant) is relatively high compared to setup costs, then the effort to minimize scrap is justified.

The very nature of the causal triggers in question make them unavoidable in real life. A production control strategy on batches, batch sizes, and batch timing is a quantitative approach to the problem. However, several qualitative measures can also be taken in order to reduce the risk associated with these types of events may have, or reduce the frequency at which they occur. Some of the possible ideas are:

1. Maintain good communication between the upper management and low-level assembly line workers. Communication can avoid errors and delays during a process.
2. Another alternative is to train and retrain the factory personnel at regular intervals so that fewer errors are made during the setup and production.

3. Study and track the process changes or other technical changes well enough to avoid unexpected events - consider all products that use a specific machine or process and discuss any side effects or dependencies.
4. Make sure that the machines and personnel can handle new products, materials, or processes before starting the actual production.

In a perfect world, these four suggestions would probably be sufficient to reduce or eliminate most, if not all, of the causal triggers. However, it is assumed that most factories are not perfect or that the scheduler has little or no control over the industrial engineering process, personnel training, and other such activities. The scheduler will have to deal with the situations, as they exist to a large degree. It is towards this end that the quantitative research on anticipatory batch insertions - number of batches, and the batch sizes - is undertaken. The next chapter presents a literature review on the relevant lot-sizing research.

CHAPTER 3

LITERATURE REVIEW

Lot-sizing policies are an integral part of the supply chain management decision-making process. Supply Chain Management can be defined as an attempt to coordinate processes involved in producing, shipping, and distributing products. An inefficient supply chain system can cause significant losses in money and customer relationships. A lot-size can be defined as the quantity produced or ordered in a given period, and it is very important to choose an appropriate lot–size as it affects almost all the costs associated with production and storage.

The modern era of research on optimal or close to optimal lot-sizes started in the mid 1950s (Wagner and Whitin, 1958). This topic is still very active (e.g., Grosfeld-Nir and Gerchak, 2004) because of its potential contribution to costs. Unfortunately, finding an optimal solution to a lot-sizing problem is generally NP hard due to issues such as the cost structure, quantity discounts, and demand distributions. The objectives for lot-sizing models are also different across different types of industries. Some industries may focus on minimizing cost in finished goods, while others focus on reducing flow-times and work-in-process.

Research on lot-sizing problems with respect to production and procurement can be broadly classified into two categories. The first category is a group of problems with known production rates. This case carries the assumption that the output of a production process is fixed, accurately predictable, or is known with certainty. This assumption holds true when the production process is completely efficient and there is zero probability of any external risk. The assumption can also be valid in cases where the risk involved is minimal and can be recovered from easily.

The second category is more realistic and it deals with cases where the production process is not repeatable or predictable (i.e. output has a random element). This category is applicable to certain type of industries where having perfect material or perfect production processes is almost impossible. Some examples include electronic fabrication and chemical processes. Three main challenges with modeling random yield problems are modeling costs affected by random yields, modeling of yield uncertainty, and measures of performance (Yano and Lee, 1995).

In both of the categories mentioned above, lot-sizing decisions can be further subdivided based on different problem objectives such as minimizing cost, satisfying due dates and improving quality. Sections 3.1 and 3.2 discuss lot-sizing models with deterministic and stochastic production processes respectively. Section 3.3 shows the methodologies used in general to solve for lot-sizing or scheduling problems and the last section provides a summary.

3.1 Lot-Sizing When Yield Is Deterministic

Reviewing the literature on lot-sizing shows that a considerable amount of work has been done on scenarios where production rates are known. In fact, many sophisticated procedures are available to solve these kinds of problems to optimality (Yano and Lee, 1995). The objectives and problem characteristics differ between the procedures. Most of the earlier work focused on minimizing cost. Costs have included aspects such as setup cost, production cost, holding cost and tardiness costs; although not all forms of costs are incorporated in all models. Some lot-sizing decisions are also based on satisfying due dates. The literature suggests that material requirement planning (MRP) systems typically focus on satisfying due dates. Brief descriptions of the work done on the problems categorized by the two main objectives are detailed below.

Minimizing Cost Objective

Some of the earlier problem formulations on lot-sizing decisions concentrated on minimizing cost. *Wagner-Whitin algorithms*, *Silver Meal Heuristics*, and *Least Cost Heuristics* (Nahmias, 2000) were some of the earliest algorithms developed to output lot-sizing policies that minimized cost. These algorithms become computationally infeasible, as the number of periods for decision-making grow larger (Nahmias, 2000). One of the simplest lot-sizing policies still considered is the *Economic Order Quantity*. Note that all these methods assume that demand is known when the decision is made. A brief description of the above algorithms can be found in Nahmias (2000) and Silver et al. (1998).

The optimal or close to optimal solution to lot-sizing problems, with a minimizing cost objective, is mostly dependent on the structure of cost function itself. Several researchers have considered this factor in order to improve the earlier algorithms. In the paper Aggarwal and Park (1993), the authors developed a “Monge Array” resulting from a concave cost structure and the application of dynamic programming. The structure of the

Monge Array is used to develop significantly faster algorithms to solve economic lot-sizing problems. Federgruen and Lee (1990) studied discounted cost structures, and so did Xu and Lu (1998). Chan et al. (1999) developed a model that minimizes holding and ordering cost, if the total cost as well as the cost per unit is a decreasing function. M.Tzur (1991) and Wagelman et al. (1992) developed models that use cost structures to solve economic order quantity more efficiently. Linear programming, mixed integer programming, and dynamic programming are some of the mathematical approaches implemented to solve lot-sizing problems with deterministic production rates (M.Tzur, 1991; Wang and Gerchak, 1996; Zhang and Guu, 1998). Heuristics and algorithms are usually “smart” versions of earlier algorithms like the Wagner-Whitin algorithm. For example, researchers typically incorporate cost structures and demand patterns to improvise classic algorithms like Wagner-Whitin algorithm.

Due Dates

The literature on lot-sizing suggests that the lot-sizing decisions in complex systems such in MRP (Materials Requirement Planning) are still mainly based on satisfying due dates. MRP derives demand for component sub assemblies and a production schedule of parent items or end items. The lot-sizing in MRP may be constrained by min-max rules and sizes that are multiples (e.g., round to the nearest 10,000). When not so constrained, lot-sizing decisions are mostly driven by the demand distribution and lead-time distribution. Since MRP is dynamic and constrained by many factors, simulation studies have been typically conducted to determine the best lot-sizing policy (Berry, 1972).

Researchers have studied demand patterns and have used the information to improve the performance of lot-sizing rules in MRP systems. Berry (1972) has shown that the cost performance of lot-sizing rules improves, as demand gets lumpier.

Graves (1987), Arrow et al. (1958), Love (1979), and Banks et al. (1986) give reviews of literature on lot-sizing problems with uncertain demands. Characteristics such as capacity constraints, number of machines, and number of products differ across different problems included in the research. Research has also considered both continuous and discrete type of models with respect to demand distributions.

3.2 Lot-sizing When Yield Is Random

Research on random yield is not a new topic area. Researchers and industrial engineers involved in quantitative modeling and analysis were aware of yield randomness as early as the 1950s. However, research on this type of problem was relatively sparse until the mid 1980s (Grofeld-Nir and Gerchak, 2004). The popularity of this area of research has grown remarkably in the last two decades because the manufacturers and scientists have focused on the consequences of yield randomness in manufacturing and logistics (Grosfeld-Nir and Gerchak, 2004; Yano and Lee, 1995).

Yano and Lee (1995) provide an extensive literature review on lot-sizing up to 1995. This has been used as a starting point for discussing recent developments. The next section contains a brief summary of the analysis and discussion in Yano and Lee. In addition, relevant papers published from 1995 until 2004 are discussed and analyzed. The objective of this section is to provide an overview of the work typically done in this area.

Lot-Sizing with Random Yields: A Review Summary (Yano and Lee, 1995)

Yano and Lee conducted an extensive review of quantitatively oriented approaches to determining lot-sizes when yield is random. According to their paper, the results of such models focus on the levels of variance in production that occur day to day and the results can be used to:

1. Help an operation run more effectively so that effort can be focused on improving performance, including yields.
2. Process improvement and supplier selection decisions can be assessed more accurately and effectively if the system wide effects of these decisions on yield are modeled accurately and, where appropriate, optimized.
3. Assist in capacity planning decisions when yield randomness is expected to be a long-range concern.

The models discussed in the review paper include single stage continuous systems, single stage periodic systems as well as complex manufacturing systems. Some of the modeling issues noted by Yano and Lee include; modeling of costs affected by random yield, modeling of yield uncertainty and performance measures. In particular, modeling of yield uncertainty has received the most attention in the literature. Yet, this area of yield characterization is constrained by a number of simplifying assumptions made by the researchers. For example, assumptions such as binomially distributed yield, stochastically proportional yield and geometrically proportional yield are commonly made, but the assumptions are not linked back to any empirical evidence or support. The models and assumptions can provide valuable insights into model behavior and bounds, but provide few insights for the actual practice of lot-sizing. Sometimes it is important to have a deeper understanding of the manufacturing process in order to characterize the yield process. This is because most of the risks associated with a specific production process may be directly linked to the way the products are processed and the resulting distribution may not be close to a theoretical baseline distribution (e.g., binomial or proportional). Some other drawbacks noted by Yano and Lee in their discussion on lot-sizing models with random yield included:

1. Lack of explicit consideration of the inspection process
2. Alternative recourse actions that can be taken with regard to defective items. Most papers assume that scrapping is the only recourse action possible.
3. Assumption of linear cost structure.
4. Assumption of stationary demands
5. Single product

Even with these limiting assumptions, the problem is quantitatively challenging and it is difficult for any model or concept to consistently derive good results under a variety of conditions. It is also important to note that majority of the recourse actions considered by the different papers in the review are reactive in nature, that is, the approaches considered are implemented after the defective units have been identified.

Recent Research On Lot-Sizing With Random Yield

The majority of the recent papers reviewed for the purpose of this research have concentrated on yield distributions similar to the papers reviewed by Yano and Lee. For example, Anily (1995) has developed a single-machine lot-sizing model with uniform yield and deterministic demand, whereas Zhang and Guu (1998), Guu and Liou (1999), Guu (1999) and Anily et al. (2002) have developed models, where the production distribution is assumed to be geometric in nature. Zhang and Guu (1997), as well as Wang and Gerchak (2000), consider multiple lot-sizing models with general yield distribution.

Ciarello et al. (1994) and Wang and Gerchak (2000) consider models that are constrained by variable production capacity. In this case, random yield is assumed to be the result of imperfect production processes and variable capacity, which is assumed to be a consequence of unexpected breakdowns, unplanned maintenance, uncertain repair duration, or rework of defective units. Grosfelf-Nir and Gerchak (2002) studied a similar environment with rework capability.

Grosfeld-Nir and Gerchak (1996) addressed several fundamental questions in single stage, multiple lot-sizing production environments. They note that multiple lot-sizing problems have received much attention in the recent years due to the following reasons:

1. Prevalence of production-to-order of relatively small volumes of custom made items.
2. Resurgence of interest in understanding the consequences of random yield in

manufacturing and logistics.

3. Proposal and analysis of several practically relevant yield concepts.

In their paper, Grosfeld-Nir and Gerchak (2004) also provide a review of models, analytical results, and insights pertaining to multiple lot-sizing in production-to-order environments. The papers discussed in their review assume that random yield is due to imperfect production process, material imperfections, and other external factors like temperature and humidity.

Discussion Of Literature On Lot-sizing With Random Yield

Section 3.2 has focused on random yield research. Two of the common characteristics of the papers reviewed are:

1. The tradeoffs that are analyzed are those that exist between overage costs and underage costs. Overage cost is incurred due to over production, and underage cost is incurred when the order in not satisfied.
2. Associated with the above point is that the objective functions of the papers focus on the minimization of expected costs.

As shown, traditional research has concentrated on the cost structure, and the distributions of yield or demand. The source for uncertainty in yield receives little attention. In particular, the literature does not show yield variability caused by triggers such as process changes, or material changes, which have been shown to occur in reality. Furthermore, traditional research carries the assumption that the distribution of yield is known, whereas the occurrence of causal triggers like the ones mentioned above are assumed to be completely random in nature, have insignificant disruptions, and do not follow any known distribution or predictive pattern. However, changes to materials and processes are not always random unless there is an error in the operation of the machine, or mishandling of materials, or miscommunication between personnel. The management and personnel of the manufacturing unit normally know that a vendor was changed, new workers are hired, and that new processes are introduced. The literature reviewed does not consider concepts such as creating extra batches of small sizes in the beginning, so that the risk associated with the predictable triggers defined above is absorbed by small batches, thereby reducing the number of items scrapped.

3.3 Modeling and Analysis Methodology

Morton and Pentico (1993) summarize some of the classical and modern approaches to the lot-sizing and scheduling problems. They classify the traditional approaches into two categories; computer simulation and mathematical:

1. Computer Simulation Approaches: Simulation is used to model the system under consideration. If the manufacturing system is too complex to analyze using algorithmic or analytical approaches (e.g., real MRP systems), simulation studies are sometimes implemented (Berry, 1972). Large-scale simulation is also sometimes preferred to optimal approaches when the area of study is relatively new and the objective of the experimentation is to get insights into the problem characteristics rather than finding an optimal solution (McKay et al., 2000; Black et al., 2004).

2. Mathematical Approaches: Linear programming, integer programming, dynamic programming, and mathematical heuristics/algorithms can be categorized as mathematical approaches. In recent research, dynamic programming has been widely used to analyze lot-sizing problems (Grosfel-Nir and Gerchak, 1996, 2002, 2004; Zhang and Guu, 1997, 1998). Wagner-Whitin algorithms, Silver Meal Heuristics, and Least Cost Heuristics are three other examples of mathematical algorithms.

Morton and Pentico (1993) also discussed some of the modern approaches that utilize artificial intelligence concepts such as expert systems and neural networks. Tabu search and simulated annealing are shown in their text as well. The recent papers on lot-sizing models and the papers reviewed in Yano and Lee (1995), favour mathematical approaches.

In summary, the dominant methodologies used in traditional lot-sizing policies include heuristics developed for specific kinds of problems, linear programming, integer programming, dynamic programming, and simulation models. Less common methods have also included queuing network theory (Dessauky, 1998) and the assignment method (Cosgrove et al., 1993). Considering the wide variety of modeling methods and approaches, it appears that the methodology chosen may be largely dependent on the system characteristics as well as the structure of the variables involved.

The reviewed literature suggests that when the objective of a study is to explore different characteristics of the model, sensitivity of the model parameters, or robustness of the model, simulation studies are often used. Simulation is preferred since it easily allows the exploration and alteration of the parameters involved - learning and understanding the dynamic relationships between the parameters and constructs. In addition, simulation facilitates the analysis of how the performance measure is affected (Law and Kelton, 1991). Large-scale computational simulations have also been used in production control research when precise solutions cannot be obtained and general production guidelines are desired (Morton and Pentico, 1993). As stated in the introduction chapter, the purpose of the research being conducted on anticipatory insertion of batches to mitigate risk is exploratory and preliminary. It is also in a field in which closed form or precise analytical results are not possible due to the complex nature of production characteristics. Specifically, one of the goals of the research is to explore the batch insertion strategy under varying experimental situations. Given these three observations, a similar approach used by Morton and Pentico (1993) is considered appropriate - large-scale computational experiments rather than analytical analysis.

The design and use of this large-scale simulation model is comparable to the methods used in the two papers on “Aversion Dynamics” found in the *Journal of Scheduling*. The Aversion Dynamic papers used methods found in similar heuristic research (Morton and Pentico, 1993). A brief summary of the methods used in the Aversion papers is presented below.

In McKay et al. (2000), a heuristic called “Averse-1” is developed to model a situation in scheduling with a primary event (planned or unexpected change, possible disruptions) leading to a secondary impact (machine not fixed properly, next few jobs being adversely affected). The purpose of this paper was to identify the problem and its attributes, then to provide an illustrative example to show how a solution to this problem could be approached in general.

The study explores the sensitivity of Averse-1 heuristic to schedule hardness, α recovery rates and τ_j, the impact factor. Schedule hardness defines the characteristics of due time. “α” determines the duration of the secondary impact and the impact factor, τ_j determines the magnitude of impact. The simulation study was designed to validate Averse-1 and to probe its robustness on a single static machine. Weighted tardiness was used to compare the performance of Averse-1 to other heuristics. The aversion point was set at time zero, the average processing time was 20 hours with a standard deviation of 5, and the average weight of the job was assumed to be 40 with a standard deviation of 10. Nine basic combinations of recovery and impact were tested with nine schedule hardness criteria, giving 81 basic runs. Each run was comprised of 500 job sets, and 10 jobs each in each set. Each of the 500 job sets was randomly generated according to processing time, due time, weight, and impact parameters. Separate random number streams were used for each parameter and were initiated from known seeds. The job-sets were scheduled according to five different heuristics and the results were compared.

Results were categorized according to the occurrence and non-occurrence of a disruption. This was done to see how Averse-1 performed when the impact does not occur. It was important to study both cases as the authors wanted to know if the benefits associated with Averse-1 became insignificant in cases where the impact does not occur as expected. When the impact does occur, Averse-1 outperformed other heuristics for the different recovery criteria, impact criteria and schedule hardness criteria. However, when the impact does not occur, Averse-1 performed worse than two other heuristics by a very small percentage.

Black et al. (2002) develops a heuristic called Averse-2, which is a proactive and dynamic extension of Averse-1. Three dispatch heuristics including Averse-2 were studied. Similar to the first Averse-1 paper, two major scenarios were analyzed – impact occurs as expected and disruption does not occur as expected. As in comparable heuristic research, job arrival tightness and schedule hardness was also considered.

The above factors resulted in 72 scenarios, which were translated to the 72 basic runs. Similar to Averse-1, 500 replications were made for each run. Randomization was achieved by using unique random number streams across replications and for each random number within a replication. The performance measure for each run was the weighted tardiness value, also similar to that of Averse-1.

The approach used in the anticipatory batch insertion research is similar to the methods summarized above. This is with respect to the experimental factors and the different manufacturing environments considered. The same overall experimentation strategy has been utilized, as were the concepts relating to job tightness, schedule hardness, and impact versus no impact. The next chapter describes the simulation and experimentation in greater depth.

3.4 Summary

The literature on lot-sizing models and random yield can be classified into two main categories with respect to the production process and how the production process affects yield: deterministic and stochastic production processes. The topic of anticipatory batch insertion to mitigate risk falls naturally into the stochastic category in that the variance in cost and tardiness associated with the causal triggers would appear to be stochastic if it was not specifically modeled or accounted for. If the high variance in production outcome was not anticipated and included in a plan, the variance in performance measure would appear as a spike and be reacted against.

The concept of causal triggers, the resulting high variance in production outcome, and strategies for controlling the output variance appears to be totally absent in the literature. As a result, a conservative research agenda is warranted; one that is suitable for exploratory and preliminary work. The first steps of such a conservative agenda are descriptive and should be designed to identify the major components of the phenomena under study and to describe any interrelationships between the components. For example, the relationship between the schedule characteristics and the magnitude of the risk associated with disruptions associated with causal triggers. This is the approach taken in the following chapters. The basic components of the concept are developed and a large-scale Monte Carlo simulation is performed to study the behavior and results when the concept is applied.

CHAPTER 4

CONCEPTUAL DEVELOPMENT

Causal triggers lead to disruptions that create significant yield losses, and which are associated with the changes in the status quo can be identified in the factory. One possible strategy is to create a secondary work order or job in advance of the main job that is expected to be affected. This is the *anticipatory batch insertion to mitigate risk* concept. As noted in the previous chapters, such manipulations have many tradeoff considerations in a factory setting. There are also many other factors in a real factory that can complicate the decision-making. In this chapter, a rich situation is first described, followed by a set of simplifying assumptions. Following this introduction, the basic scheduling problem, elements of the scheduling problem, conceptual model, and research questions are presented.

4.1 Problem Scope, Simplifying Assumptions

The real situation in a factory would have many machines, many steps in an operation, many products, and many other complicating factors to model. In order to conduct a preliminary study of the situation, a single-machine problem structure will be used. In a real factory, the scheduler has also to *first identify the causal trigger* and understand what work might be affected. In other words the scheduler has to identify the possibility of the jobs being scrapped. The empirical work conducted by McKay (1992) showed that this was possible. However, the scheduler or planner might not be perfect, make a false prediction, and cause an unnecessary batch to be created. Although the process of predicting will not be dealt with in this thesis, the possible sensitivity of the mitigation strategy to false predictions will be examined.

Once the prediction is made, the scheduler has three main decisions to make:

- First, how many batches to make? For example, is one extra batch sufficient to re-stabilize the process, or if two or more small batches will need to be made before all is well. It will be assumed for this research that, one batch will be sufficient to absorb the risk and allow stabilization (retrieves to normal processing). This batch is also referred to as the test batch. The topic of multiple batches is identified as an area for future research.
- Second, when should the test batch be scheduled? The scheduler may want the test batch to be made one or two weeks or several days in advance of the larger batch. This decision is likely to depend on the perceived risk, anticipated time to re-stabilize, and if additional batches might be necessary. To explore the basic concept of batch insertion, this timing is not considered to be a major factor and the second batch will be constructed within the same time period and just prior to the full batch. The timing issue can be explored in future research along with the concept of multiple batches.
- Third, how many parts should be in the test batch? In a real situation, there might be a minimum or maximum number of parts in the test batch that would be necessary. This will not affect the extra setup costs, but will affect the costs associated with materials. A 10% factor of the mean will be used in the research. If a smaller batch size is used, say one piece, this may give undue bias to the strategy. However, it is also unlikely that a test batch would need to be greater

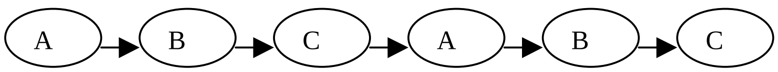
than 10% of the batch size to test out the system and re-stabilize it. The sensitivity of the strategy to the number of parts in the test batch is also identified as a possible topic for future research.

Thus, the basic problem scope will be simplified to that of a single-machine model, with a single test batch of 10% of the mean quantity to be constructed immediately prior to the main batch to be made. That is, once the scheduler has identified the possibility of a disruption due to triggers such as in introduction of change, he/she processes a test batch prior to the full production in the hope that it absorbs the risk associated with the possible disruptions. The performance of this strategy will be measured using cost and tardiness factors. The cost includes all cost associated with production and scrapping (see example in pg 33), but does not involve cost associated with the lateness of a job. Weighted tardiness on the other hand captures the lateness factor of the job-set. In addition to the sensitivity analysis of false predictions, the sensitivity of the strategy to three other key factors will be explored: i) due dates (e.g., schedule hardness), ii) sensitivity of the job to the disruptions associated with the change, and iii) the magnitude of the loss associated with the disruptions caused by causal triggers. Schedule hardness refers to the relationship between slack time in the schedule and the distribution of due dates in the job-set. For example, it is relatively easy to create a schedule with no tardiness if there are few jobs and there is slack in the schedule sufficient to cover all of the due dates (loose schedules). Schedule hardness is one of the concepts used to measure the quality of generated schedules when using weighted-tardiness measures (Morton and Pentico, 1993).

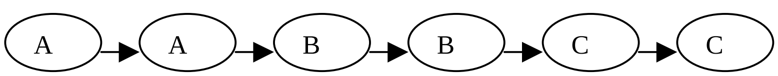
The next section describes the typical structure of the single-machine scheduling formulation when focusing on weighted tardiness.

4.2 Brief Overview Of The Single-Machine Scheduling Structure

The process of scheduling is dynamic in nature and is usually constrained by a number of factors. In order to illustrate the dynamics of scheduling and the assumptions made to simplify the model, consider a repetitive manufacturing line processing three products A, B, and C in one time period:

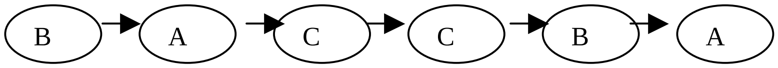


This set of six jobs of equal sizes satisfies a demand and can be called a job-set. In this simple example, all of the three products have equal demand. If A has priority over B and B has priority over C, then the schedule will look like the following diagram where two jobs with product type A is processed first and jobs with product type C is processed at the end.

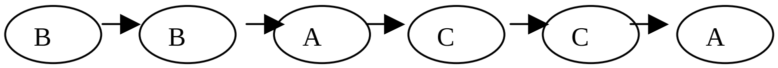


This type of grouping assumes that storage space, racks, safety stock, and such matters are not of a concern. If this grouping was encountered in a real factory, there is a probability that only three setups are required, one for each product type, provided there are no inspection or quality control issues. However, if some dispatch rule like the weighted shortest processing time (WSPT) is used, then the schedule could be of any form depending on the weight of each job. An illustration of some possible forms is presented below.

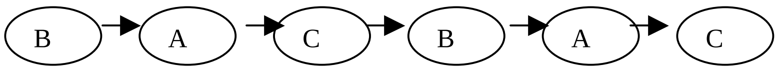
Example 1:



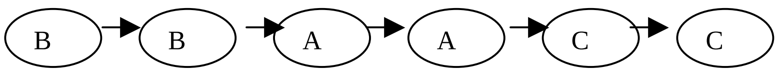
Example 2:



Example3:



Example4:



The schedule in example 1 incurs five setups, whereas the schedules in examples 2, 3 and 4 incur four, six and three setups respectively, assuming no quality control constraints. Example 3 represents the extreme case where successive jobs process different types of products and no opportunity exists to reduce the number of setups.

If the research focuses on the basic behavior of the dispatch heuristic (a heuristic that decides the sequence in which jobs are processed, based on some optimization strategy), taking advantage of setup reductions is usually ignored; examples 2 and 3 would have the same number of setups - six. Simple dispatching heuristics such as WSPT do not take sequence dependent setups into account (e.g., Morton and Pentico, 1993; Pinedo, 2002), as specific job or part knowledge is not included or addressed. The usual formulations include due date, processing time for the batch, and possible weights or penalties for tardiness. Although the batch insertion research includes setup tradeoffs and part specific information, the sequencing logic in this thesis will take the form of simple machine dispatching heuristics.

There are also assumptions about job arrivals. In the deterministic case, all jobs in the job-set are assumed to be in the work queue and any job can be worked on at any time. In the dynamic case, the jobs appear throughout the scheduling horizon at random times. The dynamic job arrival complicates the research analysis and it is reasonable to assume that deterministic job arrivals are suitable for the type of preliminary exploration being conducted in this research.

The single-machine problem formulation also assumes no state knowledge of other machines, inventory contents, or information about what happened on prior operations processed.

4.3 Elements Of The Scheduling Formulation

A job-set consists of a group of jobs processed to satisfy a demand or an order. A set of parameters define the job and the product types. Some of the elements of the formulation are deterministic or stochastic. The detailed components of the production control problem being formulated are:

Deterministic Parameters:

The following parameters are set to nominal values to create a base case for tradeoff analysis across various problem configurations. Sensitivity analysis is not conducted on these aspects of the problem formulation.

1. Setup cost: Setup cost is the cost of setting up a job (e.g. the cost of the operator or machine that sets up the job). Sequence dependent setups are not considered for the normal jobs in order to reduce setups in order to simplify the modeling and analysis. However, the setup costs after a job is inserted are altered. If a test batch is inserted and a problem does occur, the setup cost associated with the full batch is modified. It is assumed that additional effort and resources will be assigned to a job when it is run a second time after a major failure on the first attempt. This would include additional testing, supervisor attention, and so forth. It might not affect the time for setup, but the cost of the setup would be increased.
2. Setup time: Setup time is the time required to setup a job.
3. Time per piece: This is the time for processing one unit of product.
4. Cost per piece: This is the cost of processing one unit of product. This typically involves cost of operator, lubricants and other operating costs involved in processing a unit.
5. Dollar per time: Cost of spending a unit of time on the processing equipment - either for setup or for processing. An example of this parameter is the expenses which are incurred due to wear and tear or rental expenses of the machine or plant.

6. Dollar per scrap: This is the cost of scrapping one piece of product. This involves cost of raw materials used for processing and the cost of value added during processing.

Stochastic Parameters:

The stochastic parameters are those related to the sensitivity analysis conducted.

1. Due time: This parameter represents the time at which each job is due. The due time of each job is determined according to the defined schedule hardness criteria.
2. Base Quantity: Base quantity is the number of items per job.
3. Yield Loss: Yield loss is the % of units scrapped due to day to day administrative errors.
4. Job Weight: Job weight is the reduced value of the job when the job is tardy by one unit of time. This can be different for different jobs.

An example of how these parameters are used in the creation of job-sets follows:

Example Problem:

First, consider a manufacturing plant producing two types of products, A and B. In the starting description, there are no causal triggers and no abnormal scrapping levels. The example has a set of 10 jobs (job-set) in order to satisfy a known demand.

Table 4.1 Nominal Job-Set: No Causal Triggers

JOB	1	2	3	4	5	6	7	8	9	10
Product	A	A	A	B	B	A	A	A	B	B
# Pieces	100	100	100	100	100	100	100	100	100	100
#scrap	10	10	10	10	10	10	10	10	10	10

Each job has 100 pieces to process and processes only one type of product (i.e. job 1 processes only product type A and job 4 processes only product type B). On average, 10 pieces of product are scrapped due to imperfect production processes that occur randomly. Table 4.1 illustrates one possible schedule of jobs and the characteristics of each job. A list of the problem parameters and the equations for cost calculations are given below.

The cost of the job-set would be sum of the various total costs per job. Where

- Total Job Cost = setup costs (material and personnel) + cost to run the machine during the setup + material cost to make the batch quantity + cost to run the machine for the batch + any scrap costs

Let:

Setup Cost	→ SC	\$/job
Setup Time	→ ST	\$/job
Cost Per Piece	→ CP	\$/piece
Time Per Piece	→ TP	time unit/piece
Dollar Per Time	→ CT	\$/time
Dollar Per Scrap	→ CS	\$/scrapped unit

Total setup cost includes the setup cost and cost of the time associated with setup:

- Total Setup Cost = SC + (ST*CT) per job

The total production cost associated with each job is the cost of processing 100 units as well as the cost of the time associated with the production of 100 units.

- Total Production Cost = (100*CP) + (100*TP*CT) per job

Total scrapping cost is amount of money lost due to the scrapping of 10 defective units in each job.

- Total Scrap Cost = 10*CS per job

Total cost of a job is the sum of all the above costs.

- Total Cost = SC + (ST*CT) + (100*CP) + (100*TP*CT) + (10*CS) per job

If all of the setup requirements, cost factors, and times per piece were set to a nominal value of 1 for illustrative purposes, the total cost per job would be:

- Total Cost = 1 + (1*1) + (100*1) + (100*1*1) + (10*1)

  = $212

This is the total cost with nominal yield loss or nominal scrapping. Now, consider the costs if there is a causal trigger leading to a disruption and if there is one job that is sensitive to the disruption.

Let product type A be sensitive to the issues implied by a causal trigger - e.g., a material change. Assume that the disruption affects only the first job processing product type A and the magnitude of the scrapping is 100%. In other words, Job 1 loses 100 units instead of the nominal loss of ten units. The factory will react and the lost job will be replaced. Using the simplifying assumption related to sequence dependent setups, another setup is required to make up for the lost job. As a result, the costs associated with production change by:

- Total Setup Cost = Setup Cost(1) (From the first batch) + Setup Cost(2) (From the second batch)
- Total Production Cost =2*(Total Material and Processing Cost)
- Total Scrap Cost = 100*CS (From the first batch) + 10*CS (From the second batch)

If the second setup cost is assumed to be $2 while other costs and timing requirements are held constant, the total cost to complete the job is now:

- Total Cost = SC(1) + SC(2) + (2*ST*CT) + (2*100*CP) + (2*100*TP*CT) + (100*CS) + (10*CS)

  = 1 + 2 + (2*1*1) + (2*100*1) + (2*100*1*1) + (100*1) + (10*1)

  = $515

Note that the setup cost and production cost have at least doubled. Scrapping costs have also increased by 90*CS, which is ten times the nominal scrapping cost. In a real setting, the financial risks associated with such a disruption will be related to the setup, production, and scrapping costs. Consider now the application of the *anticipatory batch insertion to mitigate risk* strategy. Assume that the scheduler predicts that A will have an extreme problem the first time it is run.

The strategy suggests that an additional batch is setup before the first order for A. For illustration purposes, an additional batch with 10 pieces is setup before the first order for A. The new schedule will look like the following:

Table 4.2 Anticipatory batch insertion concept- Prediction of Variances in cost

JOB	**1**	2	3	4	6	7	8	9	10	11	12
Product	**A**	A	A	A	B	B	A	A	A	B	B
# Pieces	**10**	100	100	100	100	100	100	100	100	100	100
#scrap	**10**	10	10	10	10	10	10	10	10	10	10

Variances in cost compared to the first case:

- Total Setup Cost = SC(1) + SC(2)
- Total Production Cost = (10*CP) + (100*CP) + (10*TP*CT) + (100*TP*CT)
- Total Scrap Cost = (10*CS) + (10*CS)

The total cost would then be:

- Total Cost = SC(1) + SC(2) + (2*ST*CT) + (10*CP) + (100*CP) + (10*TP*CT) + (100*TP*CT) + (10*CS) + (10*CS)

  = 1 + 2 + (2*1*1) + (10*1) + (100*1) + (10*1*1) + (100*1*1) + (10*1) + (10*1)

  = $245

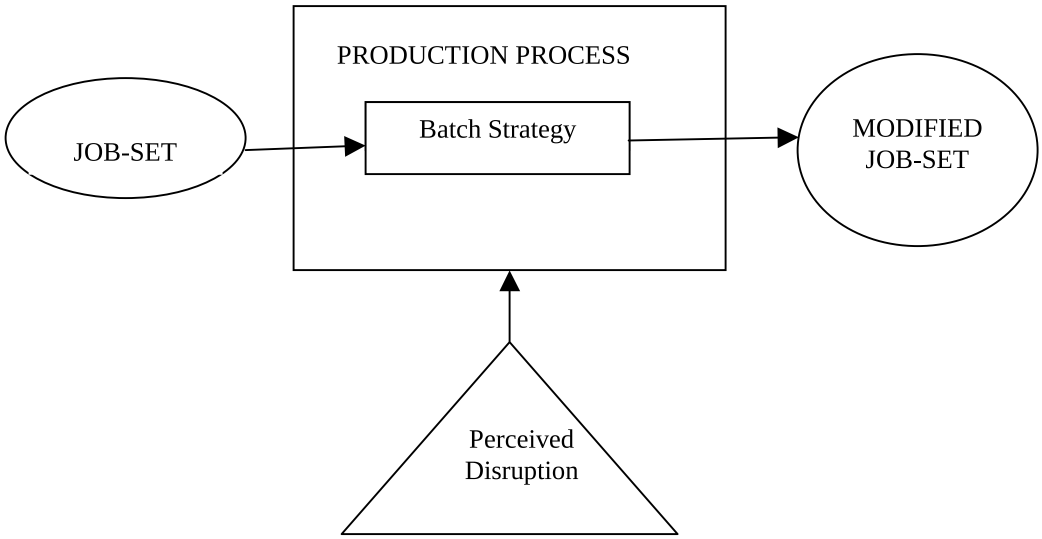
If no disruption associated with the causal trigger occurs, the cost is $212. The cost of the disruption (without any proactive strategy) is $515 - a difference of $303. If a proactive strategy is taken, the cost with an extra batch is $245 or only an increase of $33 over the base case. When the disruption occurs, the gain is obvious. When the disruption does not occur, 9 of the 10 in the first batch will go into additional stock (assuming no forward modification of the next order) and the second setup will be normal. This reduces the cost of the strategy to $235 - a difference of $23.

In this example, we did not go into tardiness and the other factors. The purpose was to simply illustrate the basic concept. The tradeoffs of false calls, schedule hardness, and so forth form the exploratory nature of the research. The following section describes the strategy in a more formal fashion.

4.4 Conceptual Framework

The conceptual framework for the anticipatory batch insertion strategy consists of four main entities, which are the initial job-set, production process, and perceived disruption, and the modified job-set. A job-set consists of a set of jobs. A single-machine, which is part of the production process, processes each job. Figure 4.1 below is a pictorial illustration of the conceptual model.

Figure 4.1 Conceptual Model



The number of pieces, job weight, due time, setup time, setup cost, time per piece, and cost per piece determine the characteristics of each job. Cost per time period and the nominal yield loss due to imperfect production processes or random capacity define the production process characteristics. Magnitude of risk defines the percentage of products lost. To explore the conceptual framework, a number of propositions have been formulated in the next section.

4.5 Research Questions and Propositions

The objective of the research is to explore various characteristics of the batch insertion strategy and evaluate the performance of the strategy under different scenarios determined by:

- Schedule hardness,
- Sensitivity of products to the disruption and
- Magnitude of risk/loss associated with the disruption.

Each scenario is compared using the cost and weighted tardiness measures.

The exploration is driven by the following five research questions. Each question is described along with its rationale. Propositions are derived based on each of the questions.

Q1. How worthwhile is it to insert a test batch if there is a disruption due to causal triggers?

Q2. What are the implications when a batch is inserted and the disruption does not occur?

Q3. How does schedule hardness affect the performance of the strategy?

Q4. How does product sensitivity affect the performance of the strategy?

Q5. How does the performance of the strategy vary with different magnitudes of risk associated with the disruption?

Each question is expanded upon in the following paragraphs.

Q1. How worthwhile is it to insert a test batch if there is a disruption due to causal triggers?

The anticipatory batch insertion strategy suggests that extra test batches are cost effective when disruptions are perceived and one or more jobs are at risk. However, setting up additional batches is costly with respect to setup costs and production costs. In addition, if the due date is tight, additional setups could cause lead-time delays. Therefore, a tradeoff exists between the benefits and costs associated with batch insertion. The risk associated with the disruption might not be significant for a manufacturing unit that produces cheap and easily recoverable items. In such situations, batch insertion for test and re-stabilization purposes might not be very profitable. In order to answer this research question we will explore the following proposition in the experimentation. Although this proposition is somewhat intuitive, it is explicitly included to establish a base case for the sensitivity analyses.

Proposition 1: The process of anticipatory batch insertion to mitigate risks will produce significant benefits for a production process that is subjected to the risks associated with the disruption.

Q2. What are the implications when a batch is inserted and the disruption does not occur?

Batch insertion for test purposes is a proactive approach and the perceived risk associated with a causal trigger cannot be predicted accurately. Sometimes a production process will run smoothly even after the introduction of a change. This can occur when quality control issues like personnel training and machine tuning is implemented properly. In the cases where the disruption does not occur as expected, the cost associated with batch insertion becomes a concern - it is an unnecessary expense and can be considered a wasteful activity. Therefore, it is important to analyze the cost factor associated with batch insertion in such an environment. The batch insertion can be viewed as a conservative or risk averse practice and the costs of this type of practice can be explored:

Proposition 2: The cost associated with batch insertion is relatively insignificant for cases where the disruption does not occur as expected.

Q3. How does schedule hardness affect the performance of the strategy?

Schedule hardness defines the due date characteristics. When a schedule is tight, there is little slack time until the order's due date. In this case, setting up additional batches could increase the job-set's total tardiness. On the other hand, if the schedule is loose there is sufficient time to complete the job-set's production. In this latter case, having additional batches in the beginning might not be a concern in terms of tardiness issues. The behavior of the strategy under different levels of schedule hardness can be explored:

Proposition 3: Batch insertion will be more beneficial for a production situation with a loose schedule provided the setup cost and/or production cost is not substantially high.

Q4. How does product sensitivity affect the performance of the strategy?

Sensitivity of a product refers to its sensitivity to the disruption associated with causal triggers such as a change in materials or machine. If a product or machine is sensitive to the casual trigger, there could be a disruption on the jobs processing that type of product. For instance, consider a manufacturing plant processing two types of products. If both product types were sensitive to the disruption, then the risk associated with the disruption would be higher when compared to the case where only one product type is sensitive. Consequently, the benefits associated with batch insertion would be higher in the first case, where both product types are sensitive to the disruption. Analyses of these factors could be useful in determining the type of industries that should consider having anticipatory batch insertion in order to mitigate the risk associated with the perceived disruption. The linearity of the strategy (linear relationship between performance of the strategy and the number of sensitive products) will be explored via:

Proposition 4: The benefits associated with batch insertion will linearly increase with an increasing number of sensitive products.

Q5. How does the performance of the strategy vary with different magnitudes of risk associated with the disruption?

The magnitude of risk is interpreted as the percentage of units scrapped due to the disruption. The highest risk associated would be the case where the entire output of a production process is lost (100% yield loss). This can happen in a manufacturing plant that produces highly sensitive products that can only be checked when the complete batch is processed. If the magnitude of risk is high, then it will be more beneficial to have batch insertions, because batches of small sizes absorb the risk associated with the disruption, which leads to scrapping fewer items. The following proposition tests the linearity of the strategy with regard to the magnitude of risk.

Proposition 5: The benefits associated with batch inserting will linearly increase for production processes that are susceptible to higher magnitudes of risk.

4.6 Summary

This chapter developed the conceptual framework and the issues for exploration. The following chapter describes the experimental design used for the exploration.

CHAPTER 5

EXPERIMENTAL DESIGN

This chapter describes the experiments used to explore the conceptual model. The simulation model and experimental framework are described in the following chapters. MATLAB software was used to implement and run the large-scale simulation model. The first section gives a brief overview of the experiment structure and a description of the approach used to conduct the experiments. The second section describes the specific experimental parameters. The third section discusses the approach used to validate the simulation model.

5.1 EXPERIMENTAL STRUCTURE

There are four structural components to this experiment. These are: Job Matrix, Experimental Scenarios, Simulation Model, and the Performance Measures. A brief description of each of the components is given below.

Job Matrix

The job matrix represents a set of jobs. Each job is created randomly according to the base quantity, due time, yield loss and job weight distributions. Once the job-set is created, the jobs in the job-set are scheduled according to the weighted shortest processing time (WSPT) rule.

Experimental Scenarios

The different experimental scenarios are determined by the experimental factors, which are schedule hardness, sensitivity of products and the magnitude of risk. A text file lists the different scenarios and the model reads in the data from the file for each run. APPENDIX A provides the list of scenarios. The simulation model calculates cost and weighted tardiness for the different scenarios considered.

Simulation Model

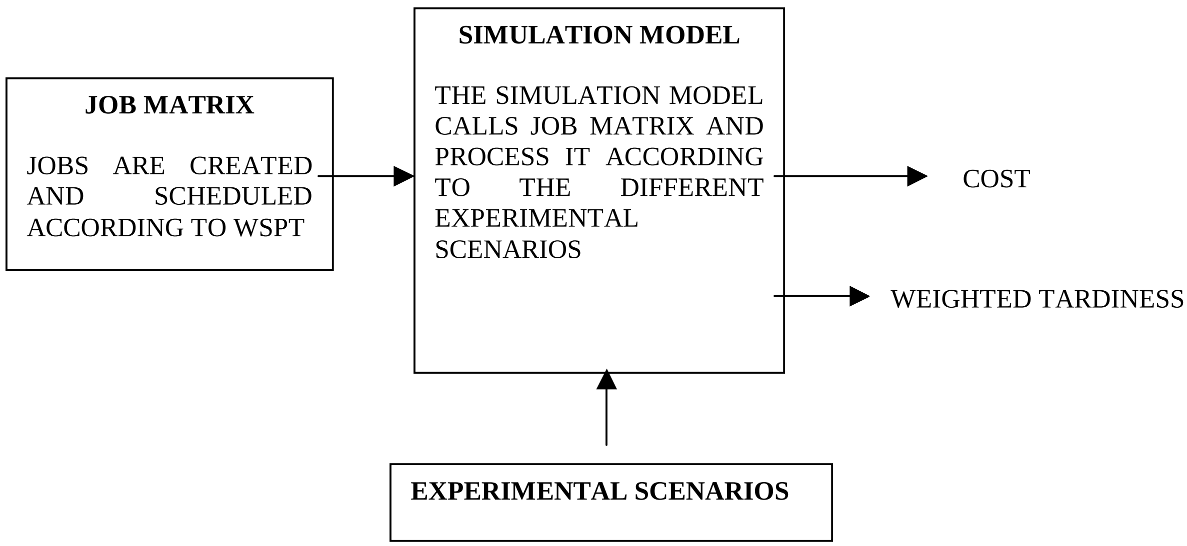
The simulation program implemented in MATLAB simulates different scenarios for the four experimental cases. They are NO DISRUPTION-NO INSERTION, DISRUPTION-NO INSERTION, DISRUPTION-INSERTION, and NO DISRUPTION-INSERTION. The program calls the job matrix, reads the experimental scenarios, processes the jobs under the different experimental cases, and calculates the cost and weighted tardiness for each scenario.

Performance Measures

The Cost and Weighted tardiness are the performance measures used to compare the performance of batch insertion under different scenarios. Weighted tardiness is the reduction in value of a job when the job becomes tardy by one unit. It is calculated according to the following equation: **max (0, completion time of job-due time)*job weight.**

Figure 5.1 illustrates the structural relationships:

Figure 5.1 Structural Components



5.2 Experimentation Design

This section describes the design specifications for each structural component of the experimentation framework, namely job matrix, experimental scenarios, simulation model, and the performance measures.

Job Matrix

The job matrix contains 500 job-sets with 10 jobs in each set. The due time, base quantity, yield loss and job weight determine the job characteristics. Each of the 10 jobs is assigned product type A or product type B with equal frequencies. The job matrix also contains any new batches created by the anticipatory batch insertion heuristic. In the case where a possible disruption is identified, an additional job is setup immediately before the first occurrence of a particular product type. The additional job is set to contain 10% of the pieces of the *original job*. All other job characteristics remain the same as that of the original job. The original job is the job with the first occurrence of the product type considered. Similarly, an additional job is setup for the second case with no anticipated disruption. However, the number of pieces in the original job is set to be 90% of the base quantity in order to avoid cases with over production since a disruption is not anticipated in this case. The settings used for the different experimental parameters are listed.

1. Due time = Normally distributed according to the schedule hardness criteria
2. Base Quantity = Normally distributed with a mean of 100 and a standard deviation of 10
3. Yield loss = Uniformly distributed between 5% to 10%
4. Job weight = Normally distributed with a mean of 40 and a standard deviation of 10 to create a coefficient of variation of 0.25

These settings are similar to the settings in the "Aversion Dynamics" papers. Separate random number streams for different experimental parameters are used to ensure independent observations.

Experimental Scenarios

The three experimental factors considered are schedule hardness, sensitivity of products and magnitude of risk. NO DISRUPTION-NO INSERTION, DISRUPTION -NO INSERTION, DISRUPTION-INSERTION, and NO DISRUPTION-INSERTION represent the different manufacturing environments analyzed. The performance of anticipatory batch insertion heuristic is analyzed under the different scenarios produced by all combinations of the experimental factors. Cost and Weighted Tardiness measure the performance. The different experimental cases and factors are analyzed in order to answer the research questions and test the propositions documented in Chapter 4. Table 5.1 below provides a summary of the research questions and the corresponding propositions. Following the table is a detailed description of the various experimental cases and factors respectively.

Table 5.1 Summary of Research Questions and Propositions

RESEARCH QUESTIONS	**PROPOSITIONS**
Q1: How worthwhile it is to insert a test batch if there is a disruption due to causal triggers.	*Proposition 1: The process of anticipatory batch insertion to mitigate risk will produce significant benefits for a production process that is subjected to the risks associated with the disruption.*
Q2: What are the implications when a batch is inserted and the disruption does not occur?	*Proposition 2: The cost associated with batch insertion is relatively insignificant for cases where the disruption does not occur as expected.*
Q3: How does schedule hardness affect the performance of the strategy?	*Proposition 3: Batch insertion will be more beneficial for a production situation with a loose schedule provided the setup cost and/or production cost is not substantially high.*
Q4: How does product sensitivity affect the performance of the strategy?	*Proposition 4: The benefits associated with batch insertion will linearly increase with an increasing number of sensitive products.*
Q5: How does the performance of the strategy vary with different magnitudes of risk associated with the disruption?	*Proposition 5: The benefits associated with batch insertion will linearly increase for production processes that are susceptible to higher magnitudes of risk.*

Experimental Cases

A description of the four experimental cases and their significance in terms of answering the research questions are given.

1. NO DISRUPTION-NO INSERTION CASE: This case represents the risk-free manufacturing environment where there is zero probability for any disruption. This case is referred to as the production process being in its normal state. Comparing this case to the others assists with understanding the significance of the causal triggers and analyzing the performance of anticipatory batch insertions.

2. DISRUPTION-NO INSERTION CASE: The system in this case does not perform a batch insertion, but the disruption still occurs. This case shows the significance of the disruption caused by causal triggers in a “normal” production environment - one which has not implemented any proactive measures to reduce the risks associated with the causal triggers. It is important to see the effects of such disruptions and decide on whether such situation requires considerable attention. The effects of the disruption are tested under various scenarios to see if there is a need to implement any risk mitigation techniques for every scenario. This will help answer ***Q1*** of the research questions. The implications of ***Proposition 1*** can also be tested using the results from the sensitivity analysis.

3. DISRUPTION -INSERTION CASE: This is the case where a disruption occurs, but batch insertion heuristic is employed to mitigate the risk associated with the disruption. The results obtained from this case are analyzed to see if the

implementation of batch insertion produces benefits when a disruption occurs. It is necessary to know under which scenario batch insertion provides the most benefits. Analyses of the results obtained from the various scenarios will provide evidence to support or refute ***Q1*** and ***Proposition 1***.

4. NO DISRUPTION-INSERTION: This case models a system where batch insertion is executed, but the disruption does not occur as predicted. This environment indicates how much additional cost is incurred with batch insertion when a disruption does not occur. Analyses of the results obtained from this case can be used to verify the significance of costs associated with batch insertions. The data is also used to investigate Q2 and ***Proposition 2***.

Experimental Factors

The four experimental cases are tested under different scenarios as defined by the three experimental factors, which are schedule hardness, sensitivity of products and the magnitude of risk. A description of the three experimental factors and the different criteria considered for each is derived below.

SCHEDULE HARDNESS: The tardiness factor (TF) and the range of due date factor (RDD) is used to set due dates with different hardness criteria (McKay et al., 2001).

TF= $1-d_{avg}/\Sigma_j p_j$. When TF is close to one, due dates are tight and if it is close to 0, due dates are loose.

RDD= $(d_{max}-d_{min})/\ \Sigma_j p_j$. Due date ranges are wide if RDD is high, and are narrow if RDD values are low.

Therefore, the TF and RDD determine the mean and standard deviation values of the due dates respectively. Three different combinations of TF and RDD values with an average processing time of 110 units is used to get 9 schedule hardness criteria. The weighted tardiness values under the nine different criteria will show how anticipatory batch insertion performs under different schedule hardness criteria. Table 5.2 shows the different factor values.

Table 5.2 Schedule Hardness Criteria

TF / RDD (Mean, STD)	**TF=.25**	**TF=0.50**	**TF=0.75**
RDD=.25	(825, 92)	(550, 92)	(275, 92)
RDD=.50	(825, 183)	(550, 183)	(275, 183)
RDD=.75	(825, 275)	(550, 275)	(275, 275)

To show an example of how the numbers in the cells are calculated, consider the entry for TF=0.25, RDD=0.25. The value of TF and the average processing time of 110 units are substituted in the equation for tardiness factor (TF) to get the average due date value of 825. Similarly, the RDD value of 0.25 and the processing time are used to get a due date range and the range is divided by three in order to obtain a standard deviation of 92. These specific values generate due dates that are loose with a narrow spread. The analysis of results obtained from the various scenarios of schedule hardness address ***Q3*** and ***Proposition 3.***

SENSITIVITY OF PRODUCTS: It is not necessary to have all products being sensitive to every kind of disruption. In the studies noted by McKay (1987, 1992) one product may be sensitive to one kind of disruption and not sensitive to other kinds. Proposition 4 stated that the performance of batch insertion would improve with an increased number of sensitive products. In order to address this issue, three different scenarios of sensitivity are considered. Analysis of the results obtained from different scenarios of sensitivity explores ***Q4*** and ***Proposition 4***.

Sensitivity Criteria

1) Only product type A is sensitive to the disruption.
2) Only product type B is sensitive to the disruption.
3) Both products, A and B are sensitive to the disruption.

MAGNITUDE OF RISK: The magnitude of risk is the percentage of the products scrapped due to disruption. Sensitivity analysis of this factor against the performance of the heuristic is done to determine if it is more beneficial to implement batch insertion in cases where high magnitude of risk is predicted. Three different scenarios are tested to see how batch insertions perform in each scenario. Analyses of the results obtained from the three scenarios are used in the investigation of ***Q5*** and ***Proposition 5***.

Disruption Criteria

1) Disruption causes 40% of items to be scrapped
2) Disruption causes 60% of items to be scrapped
3) Disruption causes 80% of items to be scrapped

These experimental factors and the different criteria considered produces 81 basic scenarios. The simulation model executes the model logic and compares the performance of anticipatory batch insertion to mitigate risk under different scenarios. The next section provides a description of the simulation model.

Simulation Design

The simulation model simulates job-sets under different scenarios and probes the robustness of the batch insertion strategy on a single machine with static jobs. For each scenario under consideration, the simulation model calls the job matrix, runs the 500 job-sets, and then outputs the total average cost and weighted tardiness values for each scenario. The different criteria considered for the three different experimental factors mentioned above give 81 basic cases for each experimental case, which was translated to 81 basic runs in the simulation design. The simulation model reads the different scenarios from a data file (Appendix A). The start time of each job is set to zero. Hence, it falls under the category of Monte Carlo simulation with static arrival of jobs. A series of pilot runs determine the set of parameter values that gives a more realistic experimentation scenario. APPENDIX C provides the MATLAB code that implements these experiments. The following settings are used for the parameters which are constant.

<u>Constant Settings</u>

Setup cost =10 units.

Setup time = 10 units.

Cost per piece = 1unit.

Time per piece = 1unit.

Dollar per time = 1unit.

Dollar per scrap = 1unit.

Performance Measures

The performance measures are average total cost and average weighted tardiness values. These are used to compare the performance of anticipatory batch insertion under different scenarios. The measurement of cost is strictly quantitative while the weighted tardiness is a qualitative measure since no cost was associated with it. Weighted tardiness values capture the lateness factor and have implications on customer satisfaction. Therefore, by using both measures, the quantitative and qualitative aspects of the problem are addressed.

5.3 Verification and Validation.

Since the performance of batch insertions under different experimental scenarios is being considered, it is important to make sure that other experimental conditions remain the same for each scenario. That is, the variations obtained should be due to the changes in the scenarios, not due to the variations in random numbers. To ensure this, the same random number streams are used across the different scenarios.

In order to validate the model logic, the batch insertion model was compared to results reported in the Aversion papers. The simulation parameters were adjusted to reflect the simple base case (i.e., equivalent to the Aversion base case) and the simulation run. The results for the WSPT heuristic were then compared. In theory, if the simulation code used random numbers and executed the heuristics correctly, the basic heuristic performance (e.g., weighted tardiness objective) should be similar. APPENDIX B contains the results of this validation step. The results are similar for WSPT and it is assumed that the basic structure and implementation of the batch insertion model is adequate for the purpose of this research.

5.4 Summary

This chapter has described the design of the experimental framework used to explore the batch insertion heuristic. The following chapter presents the results obtained during the experimentation.

CHAPTER 6

EXPERIMENTATION RESULTS

This chapter presents the results from the large-scale simulation experiments and analyzes them to determine if the results are rational and if there are any issues relating to basic validity. Chapter 7 provides a discussion on sensitivity analysis of the different experimental factors and interprets the numerical results. Within this chapter, the results are grouped according to the different experimental cases.

The first section groups the results for the different experimental cases. Analysis of each case provides insight into implication of the risks associated with causal triggers such as changes in process, product, or material. The analysis of the last two cases in particular shows the benefits associated with batch insertion given the cost of its implementation. The second section presents the results obtained from changing the schedule hardness criteria. The third section tabulates the value of performance measures under different criteria of sensitivity and the fourth section shows the performance of anticipatory batch insertion when there are different magnitudes of risk.

The assumptions and values used in all of the experiments were:

- Two products, A and B are processed by the manufacturing resource under consideration

- Sequence dependent setup is not considered. Setup costs are incurred for every batch processed.
- Setup cost = $10 per job
- Setup time = 10 time units per job
- Cost per piece = $1 per piece
- Time per piece = 1 time unit per piece
- Dollar Per Time per time = $1 per one unit of time spent in the plant
- Dollar per scrap = $1 per unit scrapped
- Due time = Normally distributed according to the schedule hardness criteria
- Base Quantity = Normally distributed with a mean of 100 and a standard deviation of 10
- Yield loss = Uniformly distributed between 5% to 10%
- Job weight = Normally distributed with a mean of 40 and a standard deviation of 10
- Total Cost of a Job = Total Setup Cost + Total Production Cost + Total Scrapping Cost.
- Weighted Tardiness of a Job = Max (0, Completion Time of Job – Due Time of Job) * Job Weight.

The following sections present the results with respect to the different experimental scenarios. Note that the results obtained are rounded off to the nearest integer value.

6.1 Results under different experimental cases

The simulation model processes 500 job-sets for each scenario determined by schedule hardness, sensitivity of products and the magnitudes of risk. The following list consists of four experimental cases in which each job-set is processed.

1. NO DISRUPTION -NO INSERTION CASE
2. DISRUPTION-NO INSERTION CASE
3. DISRUPTION-INSERTION CASE
4. NO DISRUPTION-INSERTION

The average cost and weighted tardiness values obtained for each experimental case are provided in Table 6.1. Note that all the experimental factors (i.e., schedule hardness, sensitivity of products and magnitudes of risk) vary across all experimental runs. This table represents the average result – a mix of all factors. The same variations were applied to the four experimental cases. Therefore, the results obtained from the four experimental cases are comparable to each other. **The % values in the table provide the increase in cost and weighted tardiness values for each case when compared to the base case.**

Table 6.1 Performance Measures-Experimental Cases

Performance Measures/ Experimental cases	***Average Cost ($)***	***Average Weighted Tardiness (time unit)***
No Disruption, No Insertion	2282	129660
Disruption, No Insertion	2540 (11%)	164030 (27%)
Disruption and Insertion	2367 (4%)	146660 (13%)
No Disruption, Insertion	2321(2%)	141560 (9%)

The lowest value of cost and weighted tardiness can be seen in the first row represented by the "NO DISRUPTION-NO INSERTION" case. The second case, "DISRUPTION-NO INSERTION" represents the case with highest values of cost and weighted tardiness. In this case, no risk mitigation techniques were used to reduce the effect of the disruption. These gross results intuitively match what would be expected (e.g., which case would be highest, second highest etc.). In this initial experiment, the specific values are not as important as the ordering since the main purpose of the research is to probe the relationships and sensitivity inherent in the heuristic.

6.2 Schedule Hardness

Schedule Hardness determines the characteristics of the schedule and is related to the Tardiness Factor and Range of Due Dates. Nine different scenarios of schedule hardness are considered in the analysis. The results are grouped according to different experimental cases as shown in the tables below. It is important to note that a constant set of values for the rest of the experimental factors are used. This ensures that the variations obtained in the results are consequences of changes in schedule characteristics. In this part of the study, both products are sensitive and both have the same magnitude of risk (60%).

In each of the tables below (one for each disruption/insertion case), it can be seen that the average cost remains the same with different schedule hardness criteria. This is because the cost calculated does not include any cost incurred due to tardiness factors. Thus, the results obtained aid in the validation of the implementation. The average weighted tardiness values increase as the schedule becomes tighter. **The % values are the decrease of weighted tardiness values for each case compared to the extreme case where the schedule is the tightest.**

No Disruption, No Insertion

Table 6.2 Performance Measures- Schedule Hardness (NO DISRUPTION-NO INSERTION)

Tardiness Factor (TF)	***0.25***			***0.50***			***0.75***		
Range of due date factor (RDD)	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***
Average Cost ($)	2282	2282	2282	2282	2282	2282	2282	2282	2282
Average Weighted Tardiness (time units)	14792 (89%)	18430 (86%)	24488 (81%)	51573 (60%)	56249 (57%)	63845 (51%)	116582 (10%)	122001 (6%)	129661

Disruption, No Insertion

Table 6.3 Performance Measures- Schedule Hardness (DISRUPTION-NO INSERTION)

Tardiness Factor (TF)	***0.25***			***0.50***			***0.75***		
Range of due date factor (RDD)	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***
Average Cost	2659	2659	2659	2659	2659	2659	2659	2659	2659
Average Weighted Tardiness	28573 (84%)	32731 (81%)	39705 (77%)	78311 (55%)	83644 (52%)	92279 (47%)	159174 (9%)	165675 (5%)	175042

Both Disruption and Insertion

Table 6.4 Performance Measures- Schedule Hardness (DISRUPTION- INSERTION)

Tardiness Factor (TF)	***0.25***			***0.50***			***0.75***		
Range of due date factor (RDD)	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***
Average Cost	2372	2372	2372	2372	2372	2372	2372	2372	2372
Average Weighted Tardiness	18502 (87%)	22295 (85%)	28715 (80%)	59315 (59%)	64295 (56%)	72588 (50%)	129761 (11%)	136265 (7%)	145963

No Disruption, Insertion

Table 6.5 Performance Measures- Schedule Hardness (NO DISRUPTION--INSERTION)

Tardiness Factor (TF)	***0.25***			***0.50***			***0.75***		
Range of due date factor (RDD)	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***	***0.25***	***0.50***	***0.75***
Average Cost	2322	2322	2322	2322	2322	2322	2322	2322	2322
Average Weighted Tardiness	16641 (88%)	20357 (86%)	26666 (81%)	55586 (60%)	60520 (57%)	68796 (51%)	124094 (12%)	130681 (7%)	140525

6.3 Sensitivity of Products

Sensitivity of a product defines its sensitivity to the disruptions associated with causal triggers. Three different scenarios of sensitivity are considered. As in the other tests, the simulation model evaluates the performance measures corresponding to the three different criteria, keeping other experimental factors constant. The results are grouped according to the experimental cases considered, as shown in tables 6.6-6.9. The tests were run with a medium degree of schedule hardness (TF=0.50, RDD=0.50). The magnitude of the risk was set at 60%.

No Disruption, No Insertion

Table 6.6 Performance Measures- Product Sensitivity (NO DISRUPTION-NO INSERTION)

Sensitivity (A,B) 1=Sensitive, 0=Not sensitive	***1,0***	***1,1***	***0,1***
Average Cost	2282	2282	2282
Average Weighted Tardiness	56249	56249	56249

Disruption, No Insertion

Table 6.7 Performance Measures-Product Sensitivity (DISRUPTION-NO INSERTION)

Sensitivity (A,B) 1=Sensitive, 0=Not sensitive	***1,0***	***1,1***	***0,1***
Average Cost	2471	2659	2469
Average Weighted Tardiness	69145	83644	69057

Both Disruption and Insertion

Table 6.8 Performance Measures-Product Sensitivity (DISRUPTION-INSERTION)

Sensitivity (A,B) 1=Sensitive, 0=Not sensitive	***1,0***	***1,1***	***0,1***
Average Cost	2327	2372	2327
Average Weighted Tardiness	60137	64295	60194

No Disruption, Insertion

Table 6.9 Performance Measures- Product Sensitivity (NO DISRUPTION- INSERTION)

Sensitivity (A,B) 1=Sensitive, 0=Not sensitive	***1,0***	***1,1***	***0,1***
Average Cost	2302	2322	2302
Average Weighted Tardiness	58310	60520	58383

The average cost and weighted tardiness values are generally high in the cases where the disruption occurs and both products in consideration are sensitive to the disruption compared to the cases where only one type of product is sensitive to the disruption. The two scenarios which have one sensitive product provide slightly different values for performance measures due to the difference in product characteristics.

6.4 Magnitude of Risk

The magnitude of risk is the percentage of end-items scrapped due to the disruption. Three different criteria were considered. Tables 6.10-6.13 present the results grouped under different experimental cases. The tests were run with a medium degree of schedule hardness (TF=0.50, RDD=0.50). Both products were considered sensitive to the disruption.

No Disruption, No Insertion

Table 6.10 Performance Measures- Magnitudes of Risk (NO DISRUPTION-NO INSERTION)

Magnitude of Risk	***80%***	***60%***	***40%***
Average Cost	2282	2282	2282
Average Weighted Tardiness	56249	56249	56249

Disruption, No Insertion

Table 6.11 Performance Measures- Magnitudes of Risk (DISRUPTION-NO INSERTION)

Magnitude of Risk	***80%***	***60%***	***40%***
Average Cost	2772 (9%)	2659 (4%)	2547
Average Weighted Tardiness	92023 (22%)	83644 (11%)	75668

Both Disruption and Insertion

Table 6.12 Performance Measures- Magnitudes of Risk (DISRUPTION- INSERTION)

Magnitude of Risk	***80%***	***60%***	***40%***
Average Cost	2376 (0.30%)	2372 (0.15%)	2369
Average Weighted Tardiness	64295	64295	64295

No Disruption, Insertion

Table 6.13 Performance Measures- Magnitudes of Risk (NO DISRUPTION-INSERTION)

Magnitude of Risk	***80%***	***60%***	***40%***
Average Cost	2322	2322	2322
Average Weighted Tardiness	60520	60520	60520

In the cases where disruption occurs, the cost value increases with increasing magnitudes of risk. The weighted tardiness value also increases with increasing magnitudes of risk in the second case where there was no risk mitigation techniques deployed. These changes in weighted tardiness values cannot be seen in cases where batch insertion is implemented as the earlier batches absorb the risk associated and no further delays are incurred.

6.5 Summary

This chapter presented the results obtained under different experimental scenarios and discussed the results from a validation perspective. Chapter 7 provides a discussion of the results.

CHAPTER 7

ANALYSIS AND DISCUSSION

This chapter presents the discussion of the results obtained from the simulation model. The objective of this chapter is to provide insights into the dynamics associated with various problem parameters. Section 7.1 analyses the four experimental cases and evaluates the performance of anticipatory batch insertion. Section 7.2 discusses schedule hardness and its implication on the performance of the heuristic. Sections 7.3 and 7.4 deal with the sensitivity factor and the magnitude of risk respectively.

7.1 Experimental Cases

Table 6.1 of Chapter 6 listed the average total cost and weighted tardiness values for the different experimental cases. The results indicate that the anticipatory batch insertion strategy substantially reduced the implications of the disruption. The results also showed that the cost incurred when performing batch insertion can be considerably small given the benefits associated with it.

Without implementing any risk mitigation techniques prior to the incidence of the disruption, the increase in cost ranges from 6% to 22%, and the increase in weighted tardiness range from 12% to 126%. The upper bound and the lower bound of the ranges are determined by the schedule and production characteristics. When batch insertion is employed, the cost increase due to the disruption ranges from 2% to 4% and the increase in weighted tardiness ranges from 5% to 25%, when compared to the base case of disruption and no batch insertion heuristic is employed. These values demonstrate that anticipatory batch insertion can yield substantial benefits for production environments that anticipate disruptions associated with changes in the production process. If the disruption does not occur, batch insertion and the conservative stance associated with attempting to reduce the risk costs 1% to 2% more than the nominal cost. In addition, the weighted tardiness increases from 3% to 13% of the nominal value. Table 7.1 summarizes these results.

Table 7.1 Percentage increase in Costs and Weighted Tardiness values

Experimental Case	***Percentage increase in Cost***	***Percentage increase in weighted tardiness***
Disruption -No insertion	6% - 22%	12% - 126%
Disruption - Insertion	2% - 4%	5% - 25%
No Disruption-Insertion	1% - 2%	3% - 13%

These results show that the heuristic can significantly reduce the implications associated with risks involved in production. Moreover, the costs involved in setting up the additional batches can be less significant compared to the benefits associated. Therefore, anticipatory batch insertion can provide significant benefits in the cases where risks are anticipated due to changes in the manufacturing environment. However, the overall performance of this approach can be dependent on other experimental factors like schedule hardness, sensitivity of products and magnitudes of risk. The following sections briefly discuss these factors. The above discussion suggests evidence to support the following propositions.

Proposition 1: The process of anticipatory batch insertion to mitigate risk will produce significant benefits for a production process that is subjected to the disruption associated with the causal triggers.
Proposition 2: The cost associated with batch inserting is relatively insignificant for cases where the disruption does not occur as expected.

7.2 Schedule Hardness

Tables 6.2 through 6.5 in the previous chapter grouped the results based on the nine different schedule hardness criteria for different experimental cases. The definition of schedule hardness suggests that the benefits of batch insertion would be more evident when the schedules are loose, compared to the cases where schedules are tight. In order to explore the behavior of this relationship, two extreme values and three moderate values of schedule hardness were selected. The set of criteria was.

1) (0.25, 0.25) to represent the extreme case in which the schedule is loose and the range of due date is wide
2) (0.25, 0.50) to represent the case in which the schedule is loose and the range is moderately wide
3) (0.50, 0.50) to represent the medium case in which the schedule is moderately tight and the range is moderately wide
4) (0.50, 0.75) to represent the case in which the schedule is moderately loose and the range of due date is narrow
5) (0.75, 0.75) to represent the other extreme where the due date is very tight and the range of due date is narrow.

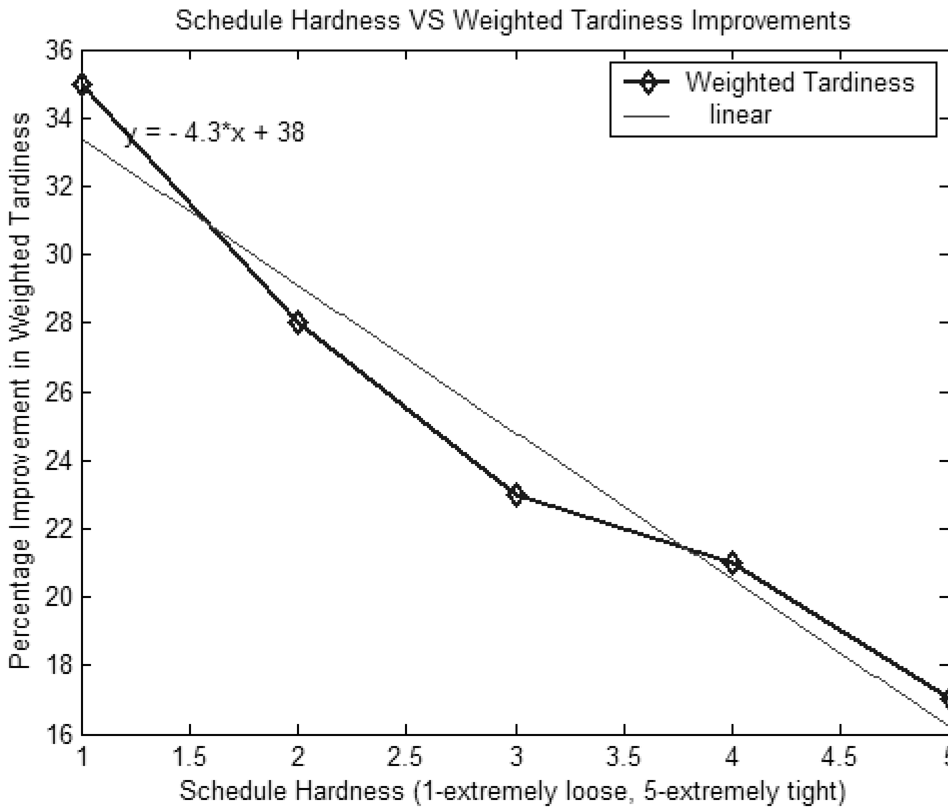
The performance measures were evaluated for the above five criteria. The variations in the results are consequences of the variations in the schedule hardness criteria since constant settings are used for other experimental factors. Note that schedule hardness only influences the tardiness values, because there are no costs associated with tardiness. Table 7.2 presents the percentage improvement in weighted tardiness values due to the implementation of anticipatory batch insertion, compared to the case where no risk mitigation techniques were implemented.

Table 7.2 Schedule Hardness-Weighted Tardiness

Schedule Hardness (TF, RDD)	***(0.25, 0.25)***	***(0.25, 0.50)***	***(0,50, 0.50)***	***(0.50, 0.75)***	***(0.75, 0.75)***
Percentage improvement in weighted tardiness values	35	28	23	21	17

The results suggest that batch insertion performs the best when the schedule is loose and the improvement in performance decreases as the schedule gets tighter. Figure 7.1 illustrates the rate at which the performance deteriorates given the experimental settings.

Figure 7.1 Schedule Hardness VS Performance Improvement



The above figure does not indicate a strict linear relationship between the schedule characteristics and performance of batch insertion. However, the figure does not indicate any significant trends, nor negative improvement in any of the cases. Therefore, it is reasonable to observe that the implementation of the batch insertion heuristic provides positive improvements across the schedule hardness criteria. This observation is possible because both extremes of schedule hardness ((0.25, 0.25) and (0.75, 0.75)) were considered. The variations in slope from one point to the next suggest the potential for further research into the relationship, but this analysis is beyond the scope of the initial research. The linear interpolation of the data gives the following results:

Equation of the straight line fitting→ y= -4.3x+38
Norm of residuals = 2.8107

The "norm of residuals" implies the goodness of fit. The smaller the value, the better is the fit. The norm of residual value in this case represents an average fit. Since batch insertion in this experimentation does not illustrate negative improvements, support exists for the following proposition:

> *Proposition 3: Batch inserting will be more beneficial for a production situation with a loose schedule provided the setup cost and/or production cost is not substantially high.*

7.3 Sensitivity of Products

Tables 6.6 through 6.9 documented the improved performance of anticipatory batch insertion with increasing number of sensitive products. Table 7.3 summarizes the percentage improvement due to batch insertion, for each scenario considered.

Table 7.3 Sensitivity of Products-Improvement in performance (Two Products)

Number of Sensitive products	***1***	***2***
Percentage improvement in Cost due to batch insertion	6	11
Percentage improvements in weighted tardiness due to batch insertion	13	23

The percentage improvements in performance measures are much higher in the case where two products are sensitive. In order to analyze the rate of increase, a manufacturing resource is considered that produces more than two products. In particular, consider a manufacturing resource that processes five product types A, B, C, D, and E. The following settings were used: scheduling hardness - TF=0.50, RDD=0.50; magnitude of risk for each product type – 60%.

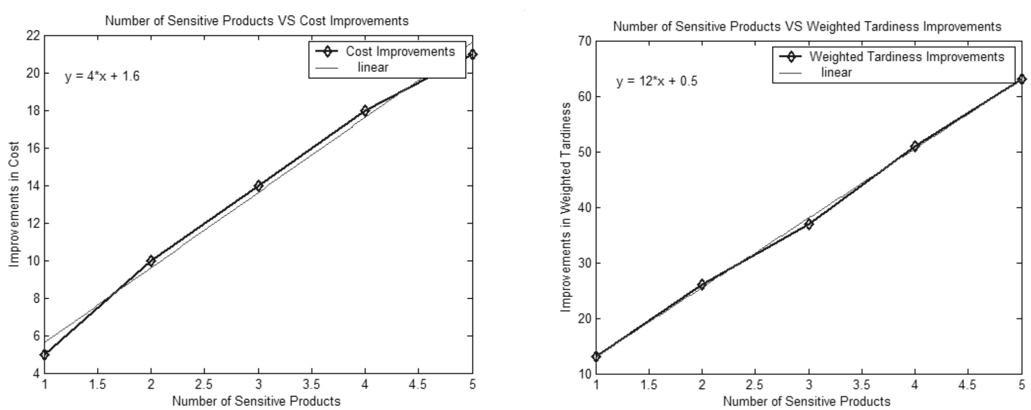
The performance improvement of batch insertion for each scenario of sensitivity, when compared to the case where no insertions are implemented is given in Table 7.4.

Table 7.4 Sensitivity of Products-Performance Measures (Five Products)

Number of Sensitive Products	***1***	***2***	***3***	***4***	***5***
Percentage improvement in Cost due to batch insertion	5	10	14	18	21
Percentage improvements in Weighted Tardiness due to batch insertion	13	26	37	51	63

The results indicate that the performance of batch insertion improves with the increasing number of sensitive products. Figures 7.2a and 7.2b represent the rate of increase in the cost and weighted tardiness values respectively.

Figure 7.2 a & b Sensitive Products VS Performance Improvements.



The above figures suggest that the number of sensitive products has a close-to-linear relationship with the performance measures, which are cost and weighted tardiness. A linear interpolation on both graphs gives the following results:

Cost Improvements:

Equation of the best fitting line→y=12x+0.5

Norm of Residuals= 1.0954

Weighted Tardiness Improvements:

Equation of the best fitting line→y=4x+16

Norm of Residuals= 1.2247

The norms of residual values are considerably small implying a good fit. Therefore, it can be reasonably concluded that the relationship analyzed is almost linear and that support exists for the following proposition:

Proposition 4: The benefits associated with batch inserting will linearly increase with an increasing number of sensitive products.

7.4 Magnitude of Risk

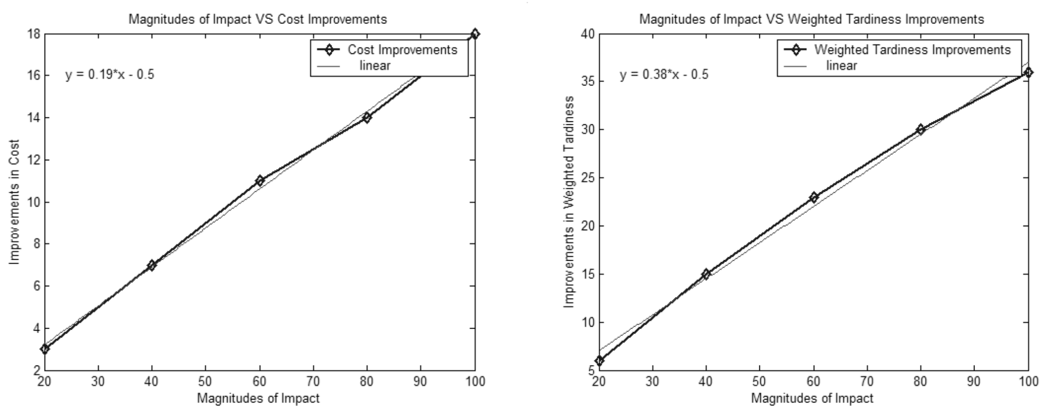
Tables 6.10 through 6.13 from the previous chapter illustrated that the performance of batch insertion with increasing magnitudes of risk. Higher magnitudes of risk imply higher number of items scrapped; consequently, the benefits associated with batch insertion will be higher since it reduces that number of products scrapped. Table 7.5 presents the performance improvements compared to the "DISRUPTION-NO INSERTION" case. Two more scenarios (20% and 100%) were added to the three considered in 7.3 to strengthen the analysis.

Table 7.5 Magnitudes of Risk-Performance Measures

Magnitude of Risk	***20%***	***40%***	***60%***	***80%***	***100%***
Percentage improvement in Cost due to batch insertion	3	7	11	14	18
Percentage improvements in weighted tardiness due to batch insertion	6	15	23	30	36

Graphs 7.3a and 7.3b illustrate the rate of increase in cost and weighted tardiness values respectively.

Figure 7.3 a & b Magnitude of Risk VS Performance Improvement



Figures 7.3a and 7.3b visually illustrate that a high magnitude of risk results in greater benefit and that the relationship is inherently linear. There is minor curvature, but the relationship can be described as being linear. The linear interpolation data is:

<u>*Cost Improvements:*</u>

Equation of the best fitting line→y=0.19x-0.5

Norm of Residuals= 0.54772

<u>*Weighted Tardiness Improvements:*</u>

Equation of the best fitting line→y=0.38x-0.5

Norm of Residuals= 1.8708

The norms of residuals are low, and this suggests that the relationship between the performance measures and the magnitudes of the risk is close to linear. Therefore, support appears to be present for the following proposition:

Proposition 5: The benefits associated with batch inserting will linearly increase for production processes that are susceptible to higher magnitudes of risk.

7.5 Summary

The analysis of the different experimental scenarios suggests that anticipatory batch insertion is: a) is most suited for a production environment that is susceptible to disruptions caused by causal triggers, produces a large number of sensitive products, and has loose schedules; and b) composed of reasonably well-behaved linear relationships between the strategy and experimental factors. The anticipatory batch insertion strategy is likely to always yield some form of positive improvements in cost and weighted tardiness when a disruption occurs. However, the percentage of improvement may not be high in cases with a low magnitude of risk and tight schedule. The next chapter tests the robustness of the model by modifying a number of the assumptions made with respect to the experimental parameters.

CHAPTER 8

EXPERIMENTAL ROBUSTNESS

The model environment described in Chapter 5 is defined by a number of constants. These include parameters such as Setup Cost, Setup Time, Time per Piece, Dollar per Time, Cost per Piece and Dollar per Scrap. This chapter explores the sensitivity and robustness issues related to four of these parameters: Setup Cost, Dollar Per Scrap, Cost per Piece and Dollar per Time.

8.1 Setup Costs

Setup Cost is the cost incurred when setting up a batch for processing. In the main experiment, it was assumed that the *additional setup cost* incurred after the occurrence of a disruption is usually higher than the nominal setup costs. This is because of the involvement of additional factory personnel, and the added caution (McKay, 1992). Five different scenarios were analyzed for this parameter. The first scenario considered the case where the cost of the extra setup is the same as the nominal setup. In the second scenario, the cost of the extra setup is 1.25 times the nominal setup. In the third case, the extra setup cost is 1.50 times the nominal setup cost. In the fourth case, an additional setup cost is 1.75 times the nominal. Lastly, in the fifth case, an additional setup cost is twice the nominal cost. Table 8.1 presents the cost increase in each case. Note, modifying setup costs do not affect tardiness values and the tardiness values are not presented. The following experimental settings were used to run the analysis: TF=0.50, RDD=0.50; both products sensitive and the magnitude of risk set to 60%. All the earlier assumptions other than the setups costs remain valid.

Table 8.1 Additional Setup Cost- Cost values

Setup cost Scenarios/ Experimental cases	***Nominal***	***1.25*Nominal***	***1.5*Nominal***	***1.75*Nominal***	***2*Nominal***
No Disruption, No Insertion	2282	2282	2282	2282	2282
Disruption, No Insertion	2659	2664	2669	2674	2679
Disruption and Insertion	2372	2372	2372	2372	2372
No Disruption, Only Insertion	2322	2322	2322	2322	2322

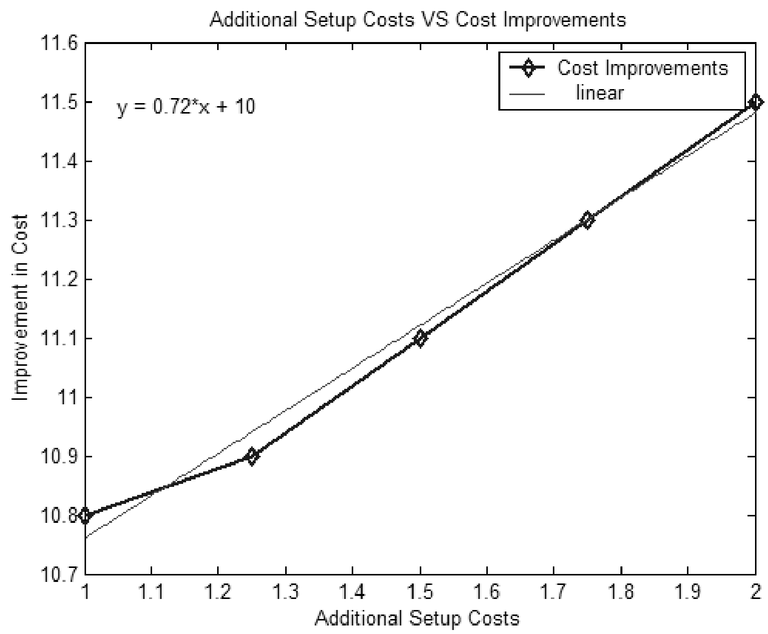
The additional setup cost affects the second row, where extra setups are made to account for the loss associated with the disruption. The extra setup cost does not affect the first and last cases since the disruption does not occur in those cases. The third case implements batch insertion and hence, no additional setup costs are incurred. The percentage improvement in cost due to the implementation of anticipatory batch insertion is provided in Table 8.2.

Table 8.2 Additional Setup Costs- Performance Improvement

Setup cost Scenarios	***Nominal***	***1.25*Nominal***	***1.5*Nominal***	***1.75*Nominal***	***2*Nominal***
Percentage improvement in cost	10.8	10.9	11.1	11.3	11.5

There is a very slight improvement in cost with increasing values of additional setups. Figure 8.1 presents the rate of increase.

Figure 8.1 Additional Setup Costs VS Cost Improvements



The results indicate a close-to-linear relationship between additional setup costs and the performance of batch insertion. The variation in slope between the first two points can be attributed to the rounding off error as the points only differ by 0.2. A linear interpolation on the data gives the following results.

Equation of the straight line fit→ y=0.72x+10
Norm of Residuals: 0.0632

The norm of residuals is significantly small. Therefore, it is reasonable to conclude that the relationship is close to linear in nature even though the rate of increase is relatively small. It is important to note that just changing the nominal setup costs in the experimental framework will not show any improvements with respect to the performance of batch insertion. This is because the number of setups does not vary in the case where anticipatory batch insertion is done to mitigate risk.

8.2 Dollar Per Scrap

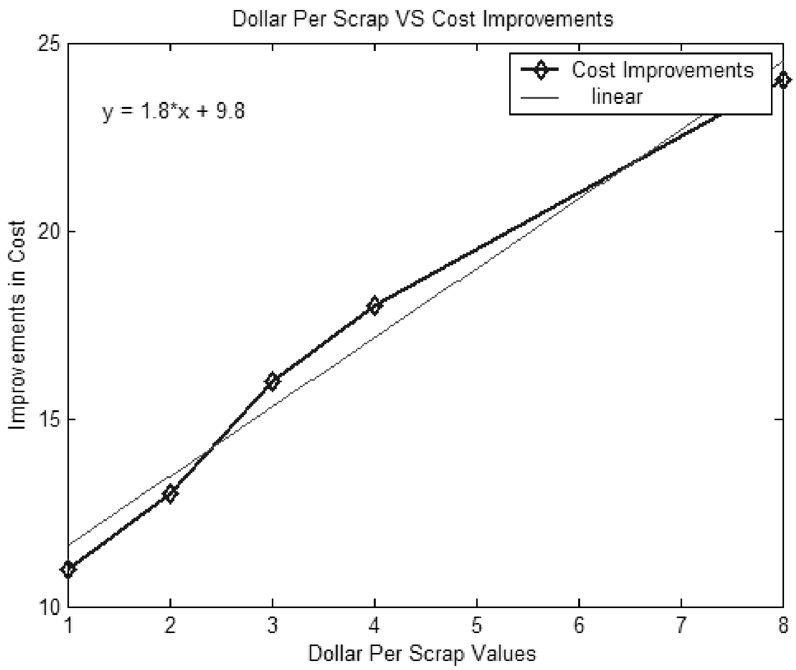
Dollar per Scrap is the scrapping value of one piece of product. This cost includes non-recoverable raw material cost, value added, and other similar operational costs. These values can be high for manufacturers when the manufactures are not able to recover the parts from the defective items. It was assumed that the value of Dollar per Scrap was one for the purpose of experimentation. In the robustness study this value was set to two, three, four, and eight. The weighted tardiness values do not change, as the scrapping value does not have any implication on the tardiness factor. Table 8.3 contains the results obtained.

Table 8.3 DollarPer Scrap- Cost Improvements

Cost per unit scrapped	***1***	***2***	***3***	***4***	***8***
Percentage Improvement in Cost	11	13	16	18	24

The test results show that improvements are higher with increasing "dollar per scrap" values. The basic trend is intuitive because batch insertion strategy is designed to reduce the number of items scrapped. The results were analyzed to determine if the relationship was linear or non-linear. Figure 8.2 shows the linear fit:

Figure 8.2 Dollar Per Scrap VS Improvement in Cost



The relationship is close to linear as can be seen from the data obtained from linear interpolation.

Equation of the straight line fit→ y=1.8x+9.8
Norm of Residuals: 1.4406

However, there is some inflection around the values of 3 and 4. While this is not significant, further analysis should be included in future research to verify this observation.

8.3 Cost Per Piece

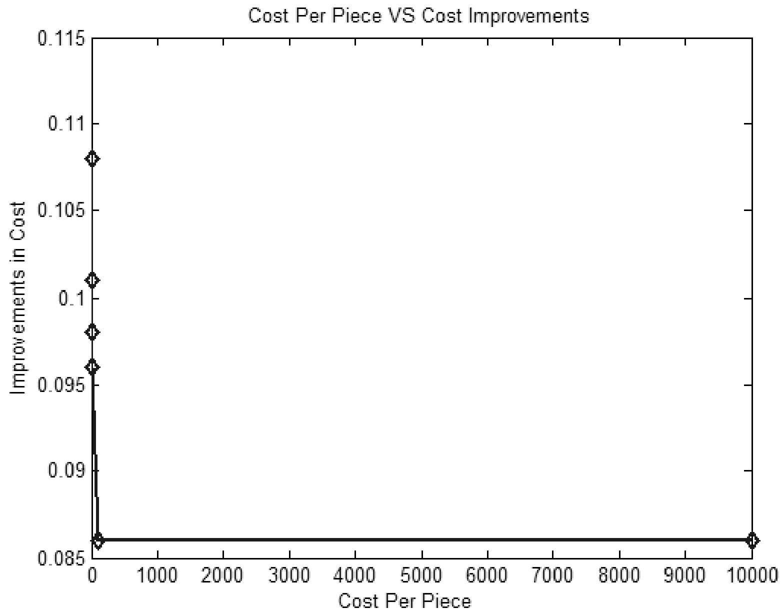
Cost Per Piece is the cost of processing one product or piece. Costs involved can be operator's wage, machine cost, lubrication cost and other costs associated with the production process. To ensure the stability of the heuristic relative to this parameter, the value was changed from one to two, three, and four. Table 8.4 summarizes the results obtained from the four scenarios. Cost per Piece does not affect tardiness value and this value is not shown.

Table 8.4 Cost Per Piece- Cost Improvements

Cost per piece value	***1***	***2***	***3***	***4***
Percentage Improvement in Cost	10.8	10.1	9.8	9.6

The improvements are decreasing slightly with increased cost per piece. Nevertheless, the rate at which it is decreasing seems to diminish with increasing value of cost. In order to see if the improvements become negative at any point, two extra runs were made with the values of 100 and 10000. At both of these values, the percentage of improvement was 8.6%. Although little can be said about the region between the two values, the results suggest that the percentage of improvement stabilizes at some point. Further investigations on this behavior should be included in any future research. Figure 8.3 presents the results of the analysis.

Figure 8.3 Cost Per Piece VS Cost Improvements



8.4 Dollar per Time

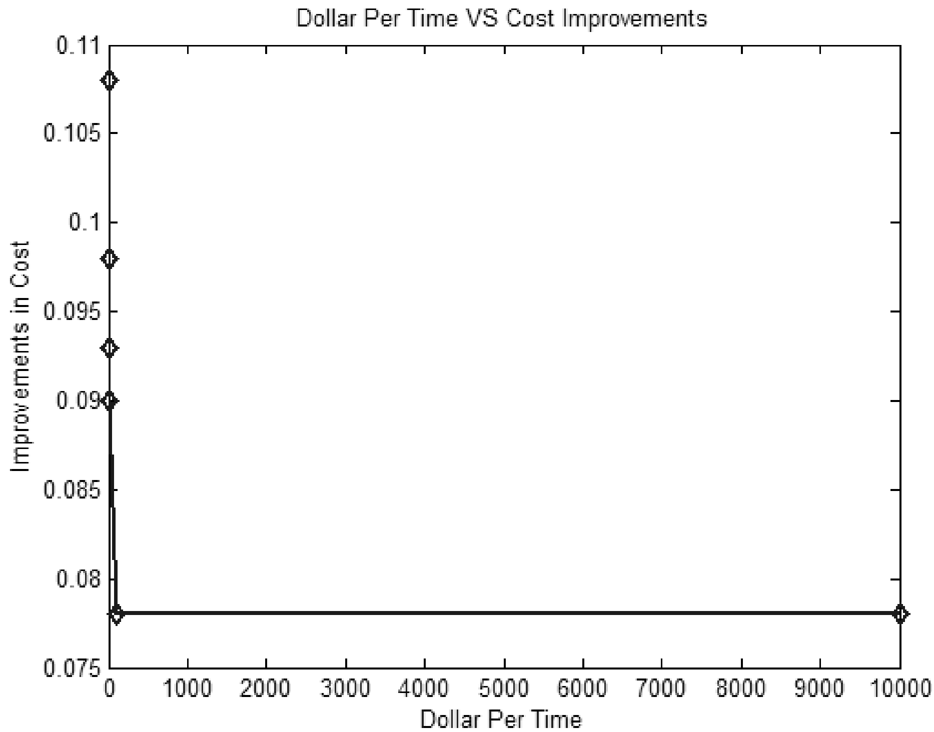
Dollar per Time is the cost of running the resource for one time unit. These values were changed from one to two, three, and four. Table 8.5 lists the improvement in performance for each scenario considered.

Table 8.5 Dollar per Time- Cost Improvements

Dollar per time	***1***	***2***	***3***	***4***
Percentage Improvement in Cost	10.8	9.8	9.3	9

The improvements are slightly reduced with increased Dollar per Time values. Similar to the case with Cost per Piece, the rate of decrease is diminishing with increased value of Dollar per Time. To see if the improvements become negative at some point, two additional runs were made with the values of 100 and 10000. Improvement in both cases was 7.8%. This result as shown in Figure 8.4 suggests that the improvement stabilizes at some point.

Figure 8.4 Dollar Per Time VS Cost Improvements



8.4 Summary

For the purposes of this initial exploration of the batch insertion heuristic, the stability of the heuristic is important; negative improvement or random results should be absent. For Setup Costs and Dollar per Scrap, the behavior appears to be linear and well-behaved. The heuristic also appears to be stable for the both Dollar per Time and Cost per Piece. However, future research should explore their leveling off of improvement.

Sensitivity analysis was not done on Setup Time, as it affects both the experimental cases: DISRUPTION-NO INSERTION, DISRUPTION-INSERTION equally. This is because the number of setups remains same in both cases. Robustness studies were also not performed on Time per Piece. Time per piece is the amount of time it takes to process a product or piece. Time per Piece and Dollar per Time complement each other. Therefore, it is not necessary to do a separate sensitivity study.

CHAPTER 9

IMPLICATIONS AND LIMITATIONS

9.1 Implications

The purpose of this thesis is to perform an exploratory and preliminary analysis of an anticipatory batch insertion strategy. Key to the concept is the assumption that certain major perturbations can be attributed to causal triggers and be predicted in advance. Several characteristics of the problem are explored: schedule hardness, product sensitivity, and magnitude of risk. The results from the simulation experiments suggest that such disruptions can cause significant losses to a manufacturing environment that does not implement any risk mitigation approach. The results also suggests that the process of anticipatory batch insertion significantly reduces the implications of such a disruption; the increase in cost and weighted tardiness associated with batch insertions is insignificant compared to the benefits it provides when a disruption occurs. Therefore, it appears reasonable to recommend anticipatory batch insertion for a production environment that has experienced high-risk disruption is anticipating yield uncertainties due to causal triggers.

The benefit associated with batch insertion is most significant when the schedule is loose. If there is sufficient time before the due date and the production environment is prone to disruptive causal triggers, making additional setups in the beginning is probably profitable. Even though batch insertion provides positive benefits for every scenario of schedule hardness, the magnitude of improvement is not very significant in the case where the schedule is tight.

The number of sensitive products also plays a critical role in the performance of batch insertion. The results suggest that batch insertion would be beneficial for a manufacturing facility that processes sensitive products. The higher the number of sensitive products, the higher the benefits associated with batch insertion. Hence, batch insertion would provide higher profits for manufacturing plants that produces a number of highly sensitive products (e.g. electronic manufacturers).

Performance of anticipatory batch insertion is also dependent on the magnitudes of risk. The performance of the strategy was shown to improve with increasing magnitudes of risk. That is, the higher the risk associated with the disruption, the more beneficial it is to do batch insertion. Therefore, it is reasonable to suggest that the anticipatory batch insertion to mitigate risk can be very profitable to a manufacturing facility facing risky disruptive events. The magnitude of risk is likely to be dependent on a number of factors, such as the type of change introduced, the level of training available for the factory personnel, and the tuning of the factory equipment.

By changing the experimental settings defined by the constant parameters, the robustness of the experimentation was tested. Different values were specified for the experimental constants. The robustness experimentation suggests that the relationships defined by the experimentation results are not altered by the different experimental settings. The relationships suggest that batch insertion can reduce the costs incurred by industries that experience risky events while producing products that have high scrapping costs - the additional batches of small sizes reduce the number of items scrapped.

9.2 Limitations

1. A limited number of experimental factors were analyzed in this thesis. The absence of a strict linear relationship between the performance of batch insertion and the experimental factors indicate the possible existence of other factors affecting its performance. These factors need to be recognized and analyzed to establish stronger relationships.
2. It is assumed that only the first batch of a product is affected by the disruption. This assumption needs to be relaxed to design a more realistic model. The time during which the batch is inserted requires more exploration.
3. The timing of inserted batches and the number of inserted batches was not explored.

CHAPTER 10

FUTURE RESEARCH AND CONCLUSIONS

10.1 Future Research

The study conducted in this thesis is exploratory and preliminary. The objective of this thesis is not the identification of an optimal solution, but is the exploration of the characteristics of the anticipatory batch insertion strategy to mitigate risks. Based on the experimental results from this first study, there are a number of factors that could be explored in subsequent research. The following sections discuss the factors associated with the assumptions used in the research.

Disruptions

For the purpose of experimentation, this thesis assumes known “magnitudes of risk”. However, in reality, this phenomenon is more uncertain in nature. The probability of a high magnitude risk could be lower than the probability of a low magnitude of risk. It is possible to use the probabilistic logic in an improved version of the simulation model. In addition, the experiment in this thesis is limited to the case where changes or such disruptions affect only the job with the first occurrence of a sensitive product type. What happens when the disruption affects more jobs? Does the timing of insertion affect the performance of the strategy? Exploring such questions could result a more realistic and more robust strategy.

Setups

It has been assumed that the setup costs and setup times are constants. Although this assumption is widely seen in the literature, there are instances where these values are stochastic. Incorporating this factor will produce a more dynamic model.

Costs

Cost per piece, cost per time and cost per unit of scrap can be considered as stochastic variables for future research.

Products

For introductory purposes, two products are considered in the majority of the experimental scenarios. Increasing the number of products and varying the sensitivity to disruptions could result in a deeper analysis.

10.2 Conclusion

In this thesis the concept of inserting a test batch to mitigate perceived risk was explored. A large scale simulation approach was used for the exploration. As the research is exploratory, a single machine with static job arrivals was used to explore the characteristics of causal triggers and to analyze the performance of batch insertion under various experimental settings.

The performance measures, the total average cost and weighted tardiness values, were used to compare the different cases. For the given experimental scenario, the results indicated that a disruption on an average could lead to 11% increase in cost and 27% increase in weighted tardiness. The highest percentage increase in cost was 22% and the highest weighted tardiness increase was 126%. The implementation of the batch insertion strategy can cause improvements in cost and weighted tardiness values when such disruptions occur. In the cases where batch insertion was implemented the highest values for percentage increase in cost and weighted tardiness were 4% and 25% respectively. When disruptions did not occur as expected, the increases in cost associated with batch insertion were shown to be relatively insignificant. The average cost and weighted tardiness increases were 2% and 9% respectively.

To explore the robustness of the strategy, three external factors were experimentally studied to find out if the performance of the strategy was sensitive to them. These were: schedule hardness, number of sensitive products and magnitude of risk. The results suggest that schedule hardness has a close to linear relationship with the performance of batch insertion. The improvement in weighted tardiness decreased as the schedule got tighter. Therefore, it is reasonable to suggest that the anticipatory batch insertion strategy performs best when the schedule is loose (35% improvement in weighted tardiness). If the costs associated with the disruption exceed late penalties, the strategy may also be useful in tight situations. The magnitude of risk also has a close to linear relationship with the performance of the strategy. The improvement due to batch insertion increases with increasing magnitudes of risk. The highest improvement was shown in the case where the magnitude of risk was 100%. The percentage improvement in this case was 36%.

A number of constants defined the experiment scenario. Sensitivity studies on these constants were performed to check if there were any changes to the relationships defined by the experimental results. The results suggest that the relationships remain valid. Further analysis is required to explore the stabilizing effects of the other constants.

In summary, this thesis took a heuristic observed in an empirical setting (McKay 1992) and explored its quantitative soundness. The exploratory research suggests that the strategy has merit in manufacturing settings that are highly susceptible to the risks associated with causal triggers. The highest return can be expected when there are slightly loose production schedules, high volumes of sensitive products are produced, there are high costs associated with the risks, and the risks can be predicted with some degree of certainty. However, the exploratory study is preliminary and it is suggested that future research be conducted on the strategy to further explore the relationships that exist in the trade-offs discussed in this thesis.

REFERENCES

1. Aggarwal, A., J. K. Park. 1993. Improved algorithms for economic lot-size problems. Oper. Res. 41(3) 549–571.

2. Anily, S. 1995. Single-machine lot sizing with uniform yields and rigid demands: robustness of the optimal solutions. IIE Trans. 27 625–633.

3. Anily, S., Beja, A., Mendel, A. 2002. Optimal lot sizes with geometric production yield and rigid demand. Operations Research 50 (3) 319-414

4. Arrow, K.J., S.Karlin, H.Scarf, 1958. Studies in mathematical theory of inventory and production. Stanford University Press, Stanford, Calif.

5. Banks, J.,W.J. Fabrycky. 1986. Procurement and Inventory Systems Analysis. Prentice- Hall, Englewood Cliffs, N.J.

6. Barad, M., Braha, D., 1996. Control limits for multistage manufacturing process with binomial yield single and multiple production runs. Journal of Operational Research society 47, 98-112

7. Beja, A. 1977. Optimal reject allowance with constant marginal production efficiency. Naval Res. Logist. Quart. 24 21–33.

8. Berry, W.L., 1972. "Lot-Sizing procedures for Requirement Planning Systems: A Framework for Analysis," Production and Inventory Management Journal 13 (2), 19-34.

9. Black, G. McKay, K., Messimer, S., 2004. Predictive, stochastic and dynamic extensions to aversion dynamics scheduling. Journal of Scheduling Volume: 7, Issue: 4, July 2004 - August 2004, pp. 277-292

10. Bregman, Robert L., 1991. Selecting Among MRP Lot-Sizing Methods for Purchased Components When the Planning Horizon Is Limited. Production and Inventory Management Journal**.** Alexandria 32, (2), p.32-40

11. Bregman, R.L., Whybark, D.c., 1982. "Materials Requirement Planning (MRP) and Purchase Discounts", Journal of Operations Management 2 (2), 137-143

12. Bregman, Whybark, D. C., 1982. "Lot-sizing Under Uncertainty in a Rolling Horizon Environment," Proceedings, Midwest Aid Conference, Milwaukee

13. Callarman, T. E. and Whybark, D. C., 1981. “Determining Purchase Quantities for MRP requirements,” Journal of Purchasing and Materials Management, 17(3) , 348-358

14. Chan, L. M. A., A. Muriel, Z. J. Shen and D. Simchi-Levi.2002. On the Effectiveness of Zero-Inventory Ordering Policies for One-Warehouse Multi-Retailer Distribution Systems with Piece-Wise Linear Cost Structures. Management Science, 48, 1446-1460

15. Chan, L. M. A., A. Muriel, Z. J. Shen, D. Simchi-Levi. 1999a. On the effectiveness of zero-inventory-ordering policies for the economic lot sizing model with piecewise linear cost structures. Technical report, North Western University, Evanston, IL.

16. Ciarello, F.W., R.Akella and T.E. Morton, 1994. A periodic review production planning model with Uncertain Capacity and Uncertain Demand- Optimality of Extended Myopic Policies. Management Sciences 40(1994) 320-332

17. Cosgrove, William J, Westerman, Robert R, Knox, John E. 1993. Optimal discrete lot sizing: A convenient approach. Production and Inventory Management Journal**.** Alexandria:. Vol. 34, Iss. 3; p. 14 - 21

18. Dessouky, M. 1998. Using queueing network models to set lot-sizing policies for printed circuit board assembly operations. Production and Inventory Management Journal. Falls Church: Vol. 39, Iss. 3; p. 38-43

19. Federgruen, A., C. Y. Lee. 1990. The dynamic lot size model with quantity discount. Naval Res. Logist. 37 707–713.

20. Gerchak, Y., Wang, Y., Yano, C.A., 1994. Lot-Sizing in assembly system with random component yields. IIE Transactions 26, 19-24

21. Goode. H.P., Saltzman. 1961. Computing Optimal shrinkage Allowances for Small Order Sizes. J. Indus. Engin. 12(1), 57-61

22. Graves, S.C.1987. Safety Stock in Manufacturing systems. J. Manuf. And Opns. Mgmt. 1(1), 67-101

23. Grosfeld-Nir, A. 1995. Single bottleneck systems with proportional expected yields and rigid demand. Eur. J. Oper. Res. 80 297–307.

24. Grosfeld-Nir, A., Y. Gerchak. 1996. Production to order with random yields: single stage multiple lot sizing. IIE Trans. 28 669–676.

25. Grosfeld-Nir, A., Y. Gerchak. 2002. Multi-Stage production to order with rework capability. Management Science. 48(5) pp 652-664.

26. Grosfeld-Nir, A., Y. Gerchak. 2004. Multiple lot-sizing in production to order. A review. Annals of Operations Research. Vol 126. p. 43-69.

27. Guu, S.M., Liou, F.R. 1999. An algorithm for multiple lot-sizing problems with rigid demand and interrupted geometric yield. Journal of mathematical analysis and applications 234, 567-579

28. Guu, S.M. 1999. Properties of multiple lot-sizing problems with rigid demand, general cost structures and interrupted geometric yield. Operations Research Letters 25, 59-65

29. Hemphill, A. D. and Whybark, D. C., 1978. "A simulation comparison of MRP Purchase discount Procedures", Discussion Paper No. 96, Indiana University

30. Laforge R.L., "MRP Lot-sizing with multiple purchase discounts", Computers and Operations research, Vol 12, No. 6, (1985), p. 579-587.

31. Law, A., Kelton, D. Simulation modeling and analysis, 1991

32. Levitan, R. E. 1960. The optimum reject allowance problem. Management Sci. 6 172–186.

33. Llewellyn, R. W. 1959. Order sizes for job lot manufacturing. J. Industrial Engrg. 10 176–180.

34. Love, S.F. 1979. Inventory Control, McGraw-Hill, NewYork.

35. McKay, K.N., 1987 Conceptual Framework. For Job Shop Scheduling. MASC Dissertation, University of Waterloo, Dept of Management Sciences.

36. McKay, K.N., 1992 Production Planning and Scheduling. PHD Dissertation, University of Waterloo, Dept of Management Sciences.

37. McKay, K., Morton, T., Ramnath, P., Wang, J. 2000 "Aversion Dynamics" Scheduling When System Changes. Journal of Scheduling 3 (2), 71-88

38. Monden, Y. 1983. Toyota Production System. Industrial Engineering and Management Press, Norcross, GA.

39. Morton, T., Pentico, D., 1993. Heuristic scheduling systems with applications to production systems and project management. Wiley-Interscience.

40. Munson, C. L., M. J. Rosenblatt. 1998. Theories and realities of quantity discounts: An exploratory study. Production Oper. Management 27(4) 352–369.

41. Nahmias, S. 2000. Production and Operations Analysis, 4th ed. Mc-Graw-Hill/Irwin, Burr Ridge, IL.

42. Nevison, C., M. Burstein. 1984. The dynamic lot size model with stochastic lead times. Management Sci. 30 100–109.

43. Noor, A., 1984. Setting Job Shop due dates with Service Level Constraints. MASC Dissertation, University of Waterloo.

44. Pinedo, M., 2002. Scheduling: Theory, Algorithms and Systems, 2nd Edition, Integre Technical Publishing Company. Inc

45. Porteus, E. L. 1986. Optimal lot sizing, process quality improvement and setup cost reduction. Oper. Res. 34 137–144.

46. Rosenblatt, M. J., H. L. Lee. 1986a. A comparative study of continuous and periodic inspection policies in deteriorating production systems. IIE Trans. 18 2–9.

47. Shaw, D. X., A. P. M. Wagelmans. 1998. An algorithm for single item capacitated economic lot sizing with piecewise linear production costs and general holding costs. Management Sci. 44(6) 831–838.

48. Silver, E. A., D. F. Pike, R. Peterson. 1998. Inventory Management and Production Planning and Scheduling, 3rd ed. Wiley, New York.

49. Tzur, M., 1991. A simple forward algorithm to solve general dynamic lot sizing models with n periods in O(nlogn) or O(n) time. Management Sci. 37 909–925.

50. Van Hoesel, C. P. M., A. P. M. Wagelmans. 2001. Fully polynomial approximation schemes for single-item capacitated economic lot-sizing problems. Math Oper. Res. 26(2) 339–357.

51. Wagelmans, A., S. van Hoesel, A. Kolen. 1992. Economic lot sizing—An O(nlogn) algorithm that runs in linear time in the Wagner-Whitin case. Oper. Res. 40 S145–S156.

52. Wagner, H. M., T. M. Whitin. 1958. Dynamic version of the economic lot sizing model. Management Sci. 5 89–96.

53. Wang, Y., Gerchak, Y., 1996. Periodic review production models with variable capacity, random yield and uncertain demand. Management Science 42, 130-137

54. Wang, Y., Gerchak, Y. 2000 Input control in a batch production system with lead times, due dates and random yields, European Journal of Operations Research 126, 371-385

55. Whybark, D. C., 1977 "Evaluating Alternative Quantity Discounts," Journal of Purchasing and Material Management, Vol 13, No2 p. 18-22

56. Xu, J., L. L. Lu. 1998. The dynamic lot size model with quantity discount: Counterexample and corrections. Naval Res. Logist. 45 419–422.

57. Yano, C. A., H. Lee. 1995. Lot sizing with random yields: a review. Oper. Res. 43 311–334.

58. Zhang, A.X., Guu, S.M., 1997. Properties of Multiple Lot Sizing model with rigid demand and general yield distribution. Computers and Mathematics with applications 33 (5), 55-65.

59. Zhang, A.X., Guu, S.M., 1998. The multiple lot-sizing problems with rigid demand and interrupted geometric yield. IIE Transactions 30, 427-431.

APPENDICES

APPENDIX A: EXPERIMENT SCENARIOS

Run	Duedate MEAN	Duedate STD	A Sensitivity	B Sensitivity	Risk Magnitude
1.	825	92	1	0	.40
2.	825	183	1	0	.40
3.	825	275	1	0	.40
4.	550	92	1	0	.40
5.	550	183	1	0	.40
6.	550	275	1	0	.40
7.	275	92	1	0	.40
8.	275	183	1	0	.40
9.	275	275	1	0	.40
10.	825	92	1	1	.40
11.	825	183	1	1	.40
12.	825	275	1	1	.40
13.	550	92	1	1	.40
14.	550	183	1	1	.40
15.	550	275	1	1	.40
16.	275	92	1	1	.40
17.	275	183	1	1	.40
18.	275	275	1	1	.40
19.	825	92	0	1	.40
20.	825	183	0	1	.40
21.	825	275	0	1	.40
22.	550	92	0	1	.40
23.	550	183	0	1	.40
24.	550	275	0	1	.40
25.	275	92	0	1	.40
26.	275	183	0	1	.40
27.	275	275	0	1	.40
28.	825	92	1	0	.60
29.	825	183	1	0	.60
30.	825	275	1	0	.60
31.	550	92	1	0	.60
32.	550	183	1	0	.60
33.	550	275	1	0	.60
34.	275	92	1	0	.60
35.	275	183	1	0	.60
36.	275	275	1	0	.60
37.	825	92	1	1	.60
38.	825	183	1	1	.60
39.	825	275	1	1	.60
40.	550	92	1	1	.60
41.	550	183	1	1	.60
42.	550	275	1	1	.60
43.	275	92	1	1	.60
44.	275	183	1	1	.60

45.	275	275	1	1	.60
46.	825	92	0	1	.60
47.	825	183	0	1	.60
48.	825	275	0	1	.60
49.	550	92	0	1	.60
50.	550	183	0	1	.60
51.	550	275	0	1	.60
52.	275	92	0	1	.60
53.	275	183	0	1	.60
54.	275	275	0	1	.60
55.	825	92	1	0	.80
56.	825	183	1	0	.80
57.	825	275	1	0	.80
58.	550	92	1	0	.80
59.	550	183	1	0	.80
60.	550	275	1	0	.80
61.	275	92	1	0	.80
62.	275	183	1	0	.80
63.	275	275	1	0	.80
64.	825	92	1	1	.80
65.	825	183	1	1	.80
66.	825	275	1	1	.80
67.	550	92	1	1	.80
68.	550	183	1	1	.80
69.	550	275	1	1	.80
70.	275	92	1	1	.80
71.	275	183	1	1	.80
72.	275	275	1	1	.80
73.	825	92	0	1	.80
74.	825	183	0	1	.80
75.	825	275	0	1	.80
76.	550	92	0	1	.80
77.	550	183	0	1	.80
78.	550	275	0	1	.80
79.	275	92	0	1	.80
80.	275	183	0	1	.80
81.	275	275	0	1	.80

APPENDIX B: RESULTS FOR VERIFICATION OF LOGIC (Compared to Averse-1)

Run	Duedatemean	Duedatestd	Avg Cost	Avg WeightedTardiness
1	150	17	615.52	2664.61
2	150	33	613.07	3291.97
3	150	50	614.29	4410.75
4	100	17	616.46	8945.71
5	100	33	615.58	9620.63
6	100	50	616.09	10828.44
7	50	17	614.79	19958.47
8	50	33	612.13	21063.80
9	50	50	618.18	22845.82
10	150	17	615.60	2678.68
11	150	33	616.91	3396.42
12	150	50	615.00	4368.85
13	100	17	615.11	8887.29
14	100	33	612.92	9530.22
15	100	50	614.13	11028.53
16	50	17	614.16	20118.27
17	50	33	615.02	21079.64
18	50	50	614.30	22180.05
19	150	17	617.53	2796.06
20	150	33	614.59	3348.59
21	150	50	611.49	4055.29
22	100	17	612.74	8616.65
23	100	33	614.27	9611.87
24	100	50	615.70	11244.64
25	50	17	617.03	20086.10
26	50	33	614.61	20811.37
27	50	50	614.91	22111.70
28	150	17	614.18	2671.92
29	150	33	618.38	3421.39
30	150	50	612.85	4177.28
31	100	17	615.99	9043.84
32	100	33	614.48	9600.21
33	100	50	613.35	10924.32
34	50	17	616.53	20189.39
35	50	33	617.07	21606.95
36	50	50	613.48	22397.75
37	150	17	613.03	2553.41
38	150	33	615.73	3299.76
39	150	50	613.69	4239.75
40	100	17	617.16	9142.57
41	100	33	615.52	9868.82
42	100	50	616.34	11426.78
43	50	17	616.25	19960.14
44	50	33	612.71	20569.63
45	50	50	613.69	22555.52

46	150	17	615.85	2735.34
47	150	33	613.85	3154.95
48	150	50	613.61	4374.99
49	100	17	617.04	8999.15
50	100	33	614.03	9636.73
51	100	50	617.29	11071.35
52	50	17	614.18	20035.41
53	50	33	616.20	21310.27
54	50	50	614.62	22869.06
55	150	17	615.55	2690.09
56	150	33	614.26	3236.76
57	150	50	614.01	4240.76
58	100	17	614.09	8752.19
59	100	33	615.70	9927.48
60	100	50	614.41	10759.15
61	50	17	614.35	20019.57
62	50	33	613.92	21066.84
63	50	50	612.62	22301.35
64	150	17	614.53	2614.48
65	150	33	615.60	3191.03
66	150	50	613.85	4296.35
67	100	17	617.13	8883.76
68	100	33	616.77	9842.48
69	100	50	614.20	10842.92
70	50	17	616.19	19889.61
71	50	33	615.03	20747.58
72	50	50	616.06	22520.11
73	150	17	615.98	2685.36
74	150	33	614.73	3111.53
75	150	50	614.17	4383.27
76	100	17	616.29	9124.55
77	100	33	612.84	9584.52
78	100	50	616.03	11059.96
79	50	17	611.98	19603.04
80	50	33	612.07	21106.27
81	50	50	616.25	22909.07
82	150	17	613.88	2664.91
83	150	33	618.07	3490.25
84	150	50	614.88	4394.40
85	100	17	615.54	8759.66
86	100	33	614.28	9741.07
87	100	50	617.13	11278.83
88	50	17	616.91	20033.73
89	50	33	612.06	20701.57
90	50	50	615.17	22515.49

APPENDIX C: MATLAB CODE

```
%Job Set Matrix is created with 500 jobsets each set containing 10 jobs.
%Created by------SMITHA VARGHESE----DEPT OF MANAGEMENT SCIENCES
%Each job has the following attributes:
%Quantity Base: The number of items in each batch
%Due time: This gives the due time and is randomly generated using schedule hardness
%Setup cost: 10 units
%Setuptime: 10 units
%Time/Piece: 1 unit
%dollarpertimeunit =1 unit
%Dollar/Scrap:1 unit per piece
%Jobweight:weight associated with each job
%Yield: 5%-10%

function varargout = splitmatrix(duedatemean, duedatestd,  jobsensitivityofA, jobsensitivityofB)
setuptime= 10;
timeperpiece=1;
jobsensitivity(1,1)=jobsensitivityofA;
jobsensitivity(1,2)=jobsensitivityofB;

%Create random number series with different seeds
%randn functions generates normal random numbers.
%rand function generates uniform random numbers.
%Different seed numbers are used for each of the stochastic
%variables so that random numbers are generated from different
%streams thus causing less bias in the outcome.

%Random numbers for base quantity.
randn(‘seed’,1);

for i=1:500
for j=1:10
basequantity(i,j)=normrnd(100,10);
end
end

%Random numbers for due time
randn(‘seed’,2);

for i=1:500
for j=1:10
duetime(i,j)=normrnd(duedatemean,duedatestd);
end
end

%Random numbers for yieldloss
rand(‘seed’,1);

for i=1:500
for j=1:10
yieldloss(i,j)=unifrnd(.05,.10);
end
end
```

```
%Random numbers for jobweight
randn('seed',3);

for i=1:500
for j=1:10
jobweight(i,j)=normrnd(40,10);
end
end

%Random numbers to determine product types
rand('seed',4);

for i=1:500
for j=1:10
uniformrandom(i,j)=unifrnd(0,1);
end
end

%creating a jobsets with specified parameters
for i=1:500

for j =1:10

% Determining the product type in the current batch when there are two types of products

if (uniformrandom(i,j) <= 0.5)
product=1;

else
product=2;
end


WSPTpar(i,j)=(setuptime+(basequantity(i,j)*timeperpiece))/jobweight(i,j); %Parameter for WSPT rules
jobsets(i,j)={[basequantity(i,j) duetime(i,j) yieldloss(i,j) jobweight(i,j) WSPTpar(i,j) product]}; %Matrix of
jobs
end
%Scheduling jobsets according to WSPT rule
WSPTparSort = sort(WSPTpar,2);

for k=1:10
m=1;
for m=1:10
% Ordering jobs in ascending order according to WSPT if jobsets{i,m}(1,5)==WSPTparSort(i,k)

jobsetsWSPT{i,k}=jobsets{i,m}; %Matrix of schduled jobs
end
end
end
end

% Creating matrix with splits done in half

for i= 1:500
k=1;
%initialing product flag
jobflag=char('F','F');
```

```
for j=1:10

producttype= jobsetsWSPT{i,j}(1,6);

if (jobsensitivity(1,producttype)==1) & (jobflag(producttype)=='F')

jobsplit{i,k}=jobsetsWSPT{i,j};
jobsplit{i,k}(1,1)=jobsetsWSPT{i,j}(1,1)*0.10;
jobsplit1{i,k}=jobsetsWSPT{i,j};
jobsplit1{i,k}(1,1)=jobsetsWSPT{i,j}(1,1)*0.10;
jobsplit{i,k+1}=jobsetsWSPT{i,j};
jobsplit{i,k+1}(1,1)=jobsetsWSPT{i,j}(1,1);
jobsplit1{i,k+1}=jobsetsWSPT{i,j};
jobsplit1{i,k+1}(1,1)=jobsetsWSPT{i,j}(1,1)*0.90;
k=k+2;
jobflag(producttype)='T';

else
jobsplit{i,k}=jobsetsWSPT{i,j};
jobsplit1{i,k}=jobsetsWSPT{i,j};
k=k+1;

end

end
NumberofJobs(i)=k-1;
end
varargout(1)={jobsetsWSPT};
varargout(2)={jobsplit};
varargout(3)={jobsplit1};
varargout(4)={NumberofJobs};
```

%Simulation Model that runs the 4 experimental cases under different scenarios.
%Created by------SMITHA VARGHESE----DEPT OF MANAGEMENT SCIENCES

```
% Reading in the scenario files
BASECASE=dlmread('BASECASESCENARIOS.txt',' ',0,0);
for q=1:243
duedatemean=BASECASE(q,2);
duedatestd=BASECASE(q,3);
N=BASECASE(q,4);
probofprod1=BASECASE(q,5);
probofprod2=BASECASE(q,6);
jobsensitivity(1,1)=BASECASE(q,7);
jobsensitivity(1,2)=BASECASE(q,8);
MagOfRisk=BASECASE(q,9);

% Calling the jobmatrix
[Job1,Job2,Job3,numberofjobs]=splitmatrix(duedatemean,duedatestd,probofprod1,probofprod2,jobsensitivi
ty(1,1),jobsensitivity(1,2));
% Experiment paramters
setupcost = 10;
setuptime = 10;
timeperpiece= 1;
dollarpertime= 1;
costperpiece= 1;
dollarperscrap= 1;


%Simulate jobsets and keep track of time.
for i=1:500
t1=0; % Initializing time for the jobset
TotJobsetCost1=0; %Initiating cost for the jobset
TotWeightedTardiness1=0; %Initiating total tardiness cost for jobset

t2=0; % Initializing time for the jobset
TotJobsetCost2=0; %Initiating cost for the jobset
TotWeightedTardiness2=0; %Initiating total tardiness cost for jobset

t3=0; % Initializing time for the jobset
TotJobsetCost3=0; %Initiating cost for the jobset
TotWeightedTardiness3=0; %Initiating total tardiness cost for jobset

t4=0; % Initializing time for the jobset
TotJobsetCost4=0; %Initiating cost for the jobset
TotWeightedTardiness4=0; %Initiating total tardiness cost for jobset

% NO SPLIT SCENARIO

%initialing product flag
jobflag=char('F','F');

for j=1:10
```

```
ProcessingTime1=setuptime+Job1{i,j}(1,1)*timeperpiece; %CompletionTime of Job
t1=t1+ProcessingTime1; %Advancing the timer t4=t4+ProcessingTime1;

SlackTime1=max(0,Job1{i,j}(1,2)-t1); %Calculate Slack Time

totsetupcost1=setupcost+setuptime*dollarpertime; %Total setup cost for batch

totprocessingcost1=Job1{i,j}(1,1)*timeperpiece*dollarpertime+Job1{i,j}(1,1)*costperpiece; %total
processing cost for batch
totwaste1=Job1{i,j}(1,1)*Job1{i,j}(1,3)*dollarperscrap; %money lost due to yield loss

CostofJob4=totsetupcost1+totprocessingcost1+totwaste1; %Total cost associated with the batch
WeightedTardiness4=max(0,t4-Job1{i,j}(1,2))*Job1{i,j}(1,4); %weighted tardiness


CostofJob1=totsetupcost1+totprocessingcost1+totwaste1; %Total cost associated with the batch
WeightedTardiness1=max(0,t1-Job1{i,j}(1,2))*Job1{i,j}(1,4); %weighted tardiness


% No Disruption

TotJobsetCost4=TotJobsetCost4+CostofJob4;

TotWeightedTardiness4=TotWeightedTardiness4+WeightedTardiness4;


%Disruption occurence

producttype= Job1{i,j}(1,6);

if jobsensitivity(1,producttype)==1 & jobflag(producttype)=='F'

CostofJob1=CostofJob1+(Job1{i,j}(1,1)-(Job1{i,j}(1,1)*Job1{i,j}(1,3)))*MagOfRisk*dollarperscrap...
+setupcost+setuptime*dollarpertime+Job1{i,j}(1,1)*MagOfRisk*timeperpiece*dollarpertime...
+Job1{i,j}(1,1)*MagOfRisk*costperpiece;

t1=t1+setuptime+(Job1{i,j}(1,1)-(Job1{i,j}(1,1)*Job1{i,j}(1,3)))*MagOfRisk*timeperpiece;
WeightedTardiness1=WeightedTardiness1+max(0,t1-Job1{i,j}(1,2))*Job1{i,j}(1,4);
jobflag(producttype)='T';
Job1{i,j}(1,7)=1;
else
Job1{i,j}(1,7)=0;
end
Job1{i,j}(1,8)=CostofJob1;

TotJobsetCost1=TotJobsetCost1+CostofJob1;

TotWeightedTardiness1=TotWeightedTardiness1+WeightedTardiness1;

end

% SPLIT SCENARIO

%initialing product flag
jobflag=char('F','F');

for j=1:numberofjobs(i)

ProcessingTime2=setuptime+Job2{i,j}(1,1)*timeperpiece; %CompletionTime of Job
t2=t2+ProcessingTime2; %Advancing the timer
SlackTime2=max(0,Job2{i,j}(1,2)-t2); %Calculate Slack Time
totsetupcost2=setupcost+setuptime*dollarpertime; %Total setup cost for batch
totprocessingcost2=Job2{i,j}(1,1)*timeperpiece*dollarpertime+Job2{i,j}(1,1)*costperpiece; %total
processing cost for batch
```

```
totwaste2=Job2{i,j}(1,1)*Job2{i,j}(1,3)*dollarperscrap; %money lost due to yield loss

CostofJob2=totsetupcost2+totprocessingcost2+totwaste2; %Total cost associated with the batch
WeightedTardiness2=max(0,t2-Job2{i,j}(1,2))*Job2{i,j}(1,4); %weighted tardiness

ProcessingTime3=setuptime+Job3{i,j}(1,1)*timeperpiece; %CompletionTime of Job
t3=t3+ProcessingTime3; %Advancing the timer
SlackTime3=max(0,Job3{i,j}(1,2)-t3); %Calculate Slack Time
totsetupcost3=setupcost+setuptime*dollarpertime; %Total setup cost for batch
totprocessingcost3=Job3{i,j}(1,1)*timeperpiece*dollarpertime+Job3{i,j}(1,1)*costperpiece; %total
processing cost for batch
totwaste3=Job3{i,j}(1,1)*Job3{i,j}(1,3)*dollarperscrap; %money lost due to yield loss

CostofJob3=totsetupcost3+totprocessingcost3+totwaste3; %Total cost associated with the batch
WeightedTardiness3=max(0,t3-Job3{i,j}(1,2))*Job3{i,j}(1,4); %weighted tardiness

%Disruption occurence

producttype= Job2{i,j}(1,6);

if jobsensitivity(1,producttype)==1 & jobflag(producttype)=='F'

CostofJob2=CostofJob2+(Job2{i,j}(1,1)-(Job2{i,j}(1,1)*Job2{i,j}(1,3)))*MagOfRisk*dollarperscrap;
jobflag(producttype)='T';

end


TotJobsetCost2=TotJobsetCost2+CostofJob2;

TotWeightedTardiness2=TotWeightedTardiness2+WeightedTardiness2;

TotJobsetCost3=TotJobsetCost3+CostofJob3;

TotWeightedTardiness3=TotWeightedTardiness3+WeightedTardiness3;

end

JobsetInfo1(i)={[TotJobsetCost1 TotWeightedTardiness1]};
JobsetInfo2(i)={[TotJobsetCost2 TotWeightedTardiness2]};
JobsetInfo3(i)={[TotJobsetCost3 TotWeightedTardiness3]};
JobsetInfo4(i)={[TotJobsetCost4 TotWeightedTardiness4]};
end
%OutPut
for i=1:500
CostVector1(i)=JobsetInfo1{i}(1,1);
WeightedTardinessVector1(i)=JobsetInfo1{i}(1,2);

CostVector2(i)=JobsetInfo2{i}(1,1);
WeightedTardinessVector2(i)=JobsetInfo2{i}(1,2);

CostVector3(i)=JobsetInfo3{i}(1,1);
WeightedTardinessVector3(i)=JobsetInfo3{i}(1,2);

CostVector4(i)=JobsetInfo4{i}(1,1);
WeightedTardinessVector4(i)=JobsetInfo4{i}(1,2);
end
% no disruption, no split
MeanCost4=mean(CostVector4);
MeanWT4=mean(WeightedTardinessVector4);

%disruption, no split
MeanCost1=mean(CostVector1);
```

```
MeanWT1=mean(WeightedTardinessVector1);

%disruption, split
MeanCost2=mean(CostVector2);
MeanWT2=mean(WeightedTardinessVector2);

%no disruption, split
MeanCost3=mean(CostVector3);
MeanWT3=mean(WeightedTardinessVector3);

runsummary1(q,1)=q;
runsummary1(q,2)=MeanCost4;
runsummary1(q,3)=MeanWT4;


runsummary2(q,1)=q;
runsummary2(q,2)=MeanCost1;
runsummary2(q,3)=MeanWT1;


runsummary3(q,1)=q;
runsummary3(q,2)=MeanCost2;
runsummary3(q,3)=MeanWT2;

runsummary4(q,1)=q;
runsummary4(q,2)=MeanCost3;
runsummary4(q,3)=MeanWT3;

end

dlmwrite(‘NODISRUPTIONNOSPLIT’,runsummary1,’\t’);
dlmwrite(‘DISRUPTIONNOSPLIT’,runsummary2,’\t’);
dlmwrite(‘DISRUPTIONSPLIT’,runsummary3,’\t’);
dlmwrite(‘NODISRUPTIONSPLIT’,runsummary4,’\t’);

meancost1=mean(runsummary1(q,2))
meanWT1=mean(runsummary1(q,3))
meancost2=mean(runsummary2(q,2))
meanWT2=mean(runsummary2(q,3))
meancost3=mean(runsummary3(q,2))
meanWT3=mean(runsummary3(q,3))
meancost4=mean(runsummary4(q,2))
meanWT4=mean(runsummary4(q,3))
```