RFID AS AN ENABLER OF IMPROVED MANUFACTURING PERFORMANCE

DISSERTATION

Presented in Partial Fulfillment of the Requirements for the

Degree Doctor of Philosophy in the Graduate School of

The Ohio State University

By

Kurt Christopher Hozak, M.A.

******

The Ohio State University

2007

Dissertation Committee:

Professor David A. Collier, Adviser

Professor James A. Hill

Professor John R. Current

Edward C. Ho, Navistar Corporate Technical Architecture Lead

Approved by

Adviser
Graduate Program in Business Administration

ABSTRACT

Radio frequency identification (RFID) is a technology that collects data by communicating between reader devices and specials tags that are attached to (or embedded inside of) objects. RFID offers several benefits compared to data collection alternatives such as bar coding, including the ability to automatically, continuously, and instantaneously track objects from many meters away, even if there is not “line of sight” between the reader devices and the tags. Among many other uses, RFID has tracked critical equipment in hospitals, shopping cart flow in stores, promotional displays and inventory across the supply chain, and equipment and containers in factories. The market for RFID systems and services is expected to be measured in billions of dollars by 2010, but despite this, aspects of RFID’s use are controversial to many companies and researchers. Compared to service processes, some analysts believe the business case for RFID for manufacturing is much more difficult. The strongly differing opinions about RFID highlight the need for research such as this dissertation that can help resolve those differences and identify when RFID use is appropriate.

The goal of this dissertation was to develop quantitative strategic and tactical insights about the justification of its use by manufacturers, particularly compared to other

data collection technologies. Early RFID research has either been qualitative or not provided much supporting quantitative and operational details. By building on classic planning and control job shop literature that provides a well-known baseline, generalizable insights about the applicability of RFID in manufacturing were developed. The multi-billion dollar manufacturer Navistar helped ground the research with real-world issues and provided close to $20,000 in support.

Simulation and repeated measures ANOVA were used to test seven hypotheses and perform additional follow-up analyses. Among the key findings:

- Flow time and tardiness performance with large lot sizes show less than one percent improvement when RFID is used instead of bar coding. In other words, given the higher cost of RFID technology, it may make more sense to use bar coding if the process is not also enhanced by using RFID's tracing capabilities to enable smaller lot sizes.
- When RFID is used in conjunction with increasingly smaller lot sizes, flow time and tardiness performance can be significantly better than when bar coding is used.
- Contrary to previous material flow literature, mean flow time and tardiness performance actually gets worse when using bar coding with very small lot sizes, thus showing the importance of modeling the data collection method (e.g., RFID versus bar coding).
- As the lot size approaches one, there are diminishing returns (in terms of flow time and tardiness improvements) associated with the use of RFID.

- When setup/processing time ratios are low, using small lot sizes results in an undesirable and disproportionately large increase in material movements compared to the flow time and tardiness performance benefits gained. Because there is little performance difference between RFID and bar coding when larger lot sizes are used, this material handling trade-off has important ramifications for the conditions where RFID use is appropriate. RFID use is more appropriate when setup times are moderate, regardless of whether the bar coding alternative is relatively fast or slow at performing data collection, or when setup times are high and the data collection alternative is relatively slow.

Dedicated to my family.

I could not have done it without you.

Thank you.

I love you.

ACKNOWLEDGMENTS

I am grateful to my dissertation committee for their help and support. Among many contributions made by them, David Collier suggested the RFID topic, guided me through the process, edited my writing, and beneficially encouraged me to strive to simplify; James Hill provided modeling and other guidance; John Current has been there with the rest of the committee when I needed them for a variety of assistance; and Ed Ho was extremely useful in providing real-world insights.

Peter Ward has been a very supportive department chair. The other Management Sciences and Quantitative Psychology faculty were also helpful in various ways, and I thank them all.

Ed Ho, Jeff Jaworski, and Karen Brinkman of Navistar provided much-appreciated financial support and access to RFID issues and data.

Bill Liebler, Ajith Kumar, Glen Rodrigues, and Tim Raimer were all excellent managers of mine before graduate school and were instrumental in developing my skills.

The Integrated Supply Management faculty at Western Michigan University, particularly Bob Landeros, Robert Reck, David Lyth, and Matthew Waller, were vital in developing my love for operations management and supply chain issues and the skill to pursue this as a career.

I am so grateful to my family for support of all kinds. In particular, all that is good about me is a reflection of my parents, Rudy and Judy Hozak. My brother, Paul Hozak, and sister, Rebecca Hozak, have been excellent role models and friends. I wish I would have had more time with you all over the past few years, and I look forward to catching up in the future!

Past OSU students have been great friends and advisers, including Gopesh Anand, Kathryn Marley, Michael Stodnick, Sean Handley, Sam Sale, Eric Olsen, Angela Lewis, Maurice Reid, Mi Kyong Newsome, Honggeng Zhou, Rachna Shah, Stephanie Eckerd, Toyin Clottey, Zhixin Liu, Liyan Hua, Carol Prahinski, and Nagesh Murthy.

Marc Posner, Cedric Sze, and the OSU Industrial, Welding, and Systems Engineering Department generously allowed me to work in their simulation lab. Bill Harper shared insights regarding different aspects of the simulation methodology.

Gary Gaukler, Gregory Heim, and Jack Hayya generously helped me think about various RFID issues and provided encouragement.

The Fisher College of Business and the Center for Operational Excellence provided financial support over the course of my studies.

There were many others who positively touched my life in large and small ways, and thus helped me complete the dissertation. I am grateful to you all.

Praise the LORD, O my soul; all my inmost being, praise his holy name.

(Psalm 103: 1)

VITA

1995…………………………………B.S., Student Planned Curriculum, Western Michigan University

1995-1996………………………….. Analyst, Andersen Consulting, Detroit, Michigan

1996-1997………………………….. Application Consulting Specialist, PowerCerv Corp., Tampa, Florida

1997-2000………………………….. Software Engineer / Senior Special Projects Engineer, Baan Company, Grand Rapids, Michigan

2000-2001………………………….. Co-Founder and Consultant, Cool Synergy, LLC, Lennon, Michigan

2001-2002…………………………..Founder and Consultant, Aspen Design, LLC, Lennon, Michigan

2002-2007………………………….. Graduate Research and Teaching Associate, The Ohio State University, Columbus, Ohio

2003…………………………………E-Training Content Developer, The Ohio State University, Columbus, Ohio

2004………………………………....ERP Systems Consultant, Navistar, Springfield, Ohio

2005-present………………………...RFID Analyst Intern, Navistar, Springfield, Ohio

FIELDS OF STUDY

Major Field: Business Administration
Concentration: Operations Management

Minor Field: Quantitative Psychology

TABLE OF CONTENTS

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

Radio frequency identification (RFID) is a technology that collects data by communicating between reader devices and specials tags that are attached to (or embedded inside of) objects. The objects can be equipment or products of a wide range of shapes and sizes (e.g., from credit cards to cables to small boxes to large shipping containers), or even animals and people can be tracked. The most common type of data that is collected is the location of each object, but temperature and other metrics can also be collected with advanced versions of the tags (McFarlane and Sheffi, 2003; Srivastava, 2004). Among many other uses, RFID has tracked critical equipment in hospitals, shopping cart flow in stores, promotional displays and inventory across the supply chain, and equipment and containers in factories (Hannon, 2005; Bonasia, 2006; Collins, 2006d; EPCglobal, 2006; Larson, Bradlow, and Fader, 2006; O'Connor, 2006a).

Even though RFID has been used for numerous applications (and proposed for many more), it is first and foremost about data collection (Woods, 2004). Analysis of RFID should therefore begin by examining its fundamental impact on collecting data.

McFarlane and Sheffi (2003) and Woods (2003) suggested that RFID should be benchmarked against bar coding and that RFID's incremental advantages should be compared to its incremental costs. Bar code systems require physically orienting labels to attain "line of sight" with a reader device. RFID systems do not have this burden because they use radio waves to automatically sense and communicate with the tags. In theory, hundreds of RFID tags can be instantaneously and simultaneously identified, compared to bar codes that may take several seconds each to be individually positioned and scanned (McFarlane and Sheffi, 2003; Kinsella, 2005). In many cases, the continuous and automatic sensing capabilities of RFID can eliminate the need for human labor in the data collection process.

The most commonly deployed RFID systems do not provide the coordinate location of an object. A single RFID reader (which can cost several hundred or more dollars) simply says whether a tag is within range or not, although more complex "arrays" of readers can be used to triangulate tagged products. More commonly, RFID readers are applied at key "chokepoints" (e.g., shipping and receiving dock doors, doors separating stock rooms from the sales floor, or other "portals") and simply record when a tracked product moves between zones or is within a reader's range. Even when used in this relatively limited manner, advocates belies that RFID's automated sensing capabilities will provide better information and operations compared to bar coding.

Bar code labels can become relatively easily damaged or obscured and thus inhibit data collection (Schuster et al., 2004; Global Commerce Initiative and IBM, 2005). In contrast, the physical structure of most RFID tags provides some protection from harsh conditions (e.g., weather, dirt, chemicals, paint, and shock), tag designs exist for especially demanding applications such as in high-temperature environments, and the tags can often be attached to the tracked product in a position where they are less likely to be damaged.

The bar codes applied to consumer goods are typically a few square centimetres in area (GS1 Canada, 2002). Most bar code readers have a range up to 30 centimetres (Joshi, 2000), whereas the RFID tags most often used in consumer environments have a maximum read range of about 10 metres under ideal conditions (Woods, 2005). These "passive tags" come without batteries and thus do not continuously broadcast a signal; instead, they are identified when they reflect back the radio waves sent by readers. This allows them to be smaller and less expensive compared to other RFID tags, but it also limits their read range. Passive tags for consumer goods are commonly several square centimetres in area and less than a millimetre thick, although much smaller passive tags are also possible (Srivastava, 2004). "Active" RFID tags have a battery that allows them to broadcast to the reader and increase the read range to over 100 metres (Woods, 2005). The trade-off for the increased read range compared to passive tags is increased size and cost. In common purchase volumes, active tags can cost tens of dollars each, compared to 10-40 cents for a passive tag embedded in an adhesive label, or under a penny for a bar code label.

The bar codes used with most consumer products typically hold from eight to a few dozen characters; less common two dimensional bar codes can hold several thousand characters (GS1 Canada, 2002). Regardless of the form of bar codes, they cannot be updated once they are printed. Even though passive tags typically have small storage capacities similar to the most common bar codes, they are designed to not only identify the *type* of product being tracked, but also the *specific unit*, unlike the most common bar codes. Passive RFID tags are increasingly supporting rewrite (update) functionality. Active RFID tags almost always support update functionality and can hold tens of thousands of characters. Beyond identifying the product type and specific unit, this is useful for carrying and storing comprehensive product and process information when a centralized information system is not available.

As described above, RFID clearly offers several benefits compared to data collection alternatives such as bar coding. Such benefits are expected to drive the market for RFID systems and services to be measured in billions of dollars by 2010 (McCrea, 2006). Despite this, aspects of RFID's use are controversial to many companies and researchers. For example, nearly all of the companies in one study believed their return on investment (ROI) from RFID would be poor (Smyrlis, 2005) and twenty percent of another survey's respondents were not sure they would *ever* see a return (Bacheldor, 2005). AMR Research observed that justification for RFID use still has not been generally demonstrated (Food Manufacture, 2005), and manufacturers in particular remain skeptical despite claims of retailer success (Hoffman, 2005; McCrea, 2006; Vijayaraman and Osyk, 2006). Even the head of EPCglobal US (the leading RFID standards organization and key champion for the technology) admitted, "Defining an ROI for this technology is hard. If the ROI was as obvious as some would like, everyone would have adopted the technology 40 years ago." (Quinn, 2005) A key concern is that other data collection methods may facilitate only slightly lower operations performance, yet cost much less.

In contrast, RFID advocates believe that RFID can be used for great advantage (Srivastava, 2004), particularly for early adopters (Ericson, 2004b; Rutner, Waller, and Mentzer, 2004; Alvarez, 2005; Lai, Hutchinson, and Zhang, 2005; Scott, 2005). Some advocates warn that instead of “playing a waiting game,” it is important that companies start using this “sure shot” technology now so they will not have to “pay the consequences” of being “left behind” and “trying desperately to play catchup” (one advocate suggested that not using RFID could lead to “premature voluntary retirement” for overly cautious managers) (Craig, 2004; Evans, 2005; Quinn, 2005; Rothfeder, 2005; Sliwa, 2005a; Sutton, 2005). The colorful verbiage used by RFID advocates is quoted here to starkly contrast with the cautious RFID outlook cited in the previous paragraph. The strongly differing opinions about RFID highlight the need for research such as this dissertation that can help resolve those differences and identify when RFID use is appropriate.

Both supporters and critics of RFID agree that there is too much at stake to make a wrong decision about the adoption of this headline-making technology. RFID systems can lead to better information, operational efficiencies, improved customer relationships, and market access, but these benefits must be traded off against obstacles related to technical immaturity, stakeholder acceptance, and the skills and financial resources required to achieve the benefits. Byrnes (2003) asserted that “Auto-ID [RFID] will produce some big winners and a lot of losers. Even for the winners, Auto-ID requires so much capital and change that the risk is very great. Successful transition management requires insight, finesse, and careful planning."

One way to identify appropriate applications of RFID is to identify where RFID's benefits are likely to be particularly useful and the tradeoffs are not so severe. Competitive pressures are forcing many companies to increase variety, reduce lead times, and improve customer service (Hayes and Pisano, 1996). Simultaneously, government and industry concerns about liability, quality, process improvement, and warranty costs are making tracking and traceability increasingly important as both an order qualifier and order winner (Florence and Queree, 1993; Steffansson and Tilanus, 2001; van Dorp, 2002; Chappell, Ginsburg, Schmidt, Smith, and Tobolski, 2003; Bacheldor, 2006a; Barlow, 2006; Jacobson, 2006). While bar-coding can help provide tracking and traceability, it adds time to the overall supply chain process, and is still generally reliant on human execution that is inherently imperfect. Because RFID's sensing capability is continuous and automatic and has essentially zero variable cost, more variety is enabled because the increased complexity can be better managed as a result of the improved information, execution, and control. Furthermore, RFID's improved information, execution, and control also facilitate the use of small lot sizes (which in turn leads to fast lead times and better service).

Lot streaming allows smaller "transfer lots" created from an initial job to move independently through a plant (Jacobs and Bragg, 1988; Litchfield and Narasimhan, 2000). Although creating relatively more transfer lots from a job has been shown to improve performance, traceability issues pose an impediment. To support a wide range of mix flexibility (product variety), the jumbled process flows of job shops are already complex and thus relatively prone to traceability and control problems. With increased transfer lots (due to smaller transfer lots) comes increased likelihood that the exact history of products will not be accurately recorded or that materials will be improperly co-mingled (Kher, Malhotra, and Steele, 2000), particularly in job shops (Litchfield and Narasimhan, 2000). Thus, companies have to consider the trade-off between increases in performance associated with increased lot streaming versus increased non-value-adding label reading time and traceability errors associated with bar coding. This dissertation explores that concern by observing that RFID technology removes a key barrier to smaller lot sizes than were previously possible, because it allows material to be automatically and continuously tracked without labor limitations. Not only is no time required to orientate products for bar code scanning, but RFID also promises to more reliably identify and track products. The dissertation also analyzes the trade-off of increased material movements compared to the reductions in flow time and proportion tardy that are driven by the use of the smaller lot sizes.

1.1 Goal of this dissertation research

The goal of this dissertation was to develop quantitative strategic and tactical insights about the justification of RFID use by manufacturers, particularly compared to other data collection technologies. Early RFID research has either been qualitative or not provided much supporting quantitative and operational details that would help in understanding how the results generalize (Gilmore and Fralick, 2005; Murphy-Hoye, Lee, and Rice, 2005). One of the basic conclusions suggested by the early analysis is that RFID is most likely to benefit companies that can use it to facilitate new ways of performing operations and logistics, thus implying that RFID should be used in conjunction with business process reengineering (BPR). Unfortunately, identifying such RFID BPR opportunities has been difficult, particularly for manufacturers (Byrnes, 2004; Ericson, 2004c; Sliwa, 2005b; McCrea, 2006; Neil, 2006; Roberti, 2006).

The difficulty in research of generalizing BPR opportunities makes it useful to study RFID in the context of familiar operational models to show how RFID can be used to enable process changes within those models. By building on classic planning and control literature that provides a well-known baseline, generalizable insights about the applicability of RFID in manufacturing can be developed. Murphy-Hoye et al. (2005) called for an increase in this style of research, noting that the current literature is lacking in studies that quantitatively show how process characteristics can change as a result of RFID's enabling functionality. Based on the logic that RFID is most likely to benefit operations that are relatively complex and unstructured (Woods, 2005), a traditional job shop with jumbled process flow was modeled by this dissertation. Grounded, real-world insights were obtained by working closely with the multi-billion dollar manufacturer Navistar, which provided close to $20,000 in support of related RFID research.

McFarlane and Sheffi (2003) and Woods (2005) noted that RFID systems must be shown to be better than the existing bar code alternative, a data collection technology that has already been demonstrated to be capable and cost-effective. Thus, the dissertation quantitatively compares operating conditions and policies that affect the relative attractiveness of RFID versus bar coding, and it examines performance trade-offs associated with ever-smaller production lots that are uniquely enabled by RFID technology. The terms “operating conditions and policies” were used by Kher et al. (2000), who called for more varieties of conditions and policies to be included as model factors in related future research, and as will be discussed in more detail in Chapter 3, this dissertation accomplishes that. An “operating condition” is a characteristic of the circumstances under which a manufacturer operates (e.g., because of its chosen product lines and processes), whereas as an “operating policy” is a decision rule used by the manufacturer. Based on their prevalence in the literature, this dissertation focuses on the operating conditions of the manufacturing setup/processing time ratio and the coefficient of variation of processing time between work centers, and the operating policies of the secondary dispatching rule and due date tightness parameter (each of these factors is discussed in more detail in sections 1.2 and 3.2). By comparing current operating conditions to the conditions shown to be appropriate for RFID use, companies can make better decisions about whether to invest in RFID or use a less expensive and complex data collection alternative. Similarly, companies that choose to use RFID will want to know if there are operating policies that can be used to maximize the value of their technology.

Companies also need confirmation of whether investment in RFID technology alone (e.g., as a bar code replacement) is enough to lead to major changes in performance, or whether processes also need to be changed in conjunction with the enabling features of RFID (e.g., using smaller lot sizes that are made possible by the technology's better tracking, traceability, and control) (Murphy-Hoye et al., 2005). In the latter case, even if a company can identify how a process should be changed, they may not have the time or operational capability to make the change, particularly if changing the process leads to undesirable side-effects. For example, RFID can enable smaller lot sizes, but material handling capabilities may need to be upgraded to support the additional material movements between work centers. RFID and smaller lot sizes might lead to better flow time and tardiness performance, but it is important for companies to understand what tradeoffs will result, and what corresponding additional investments (such as automated material handling) might be necessary to offset the tradeoffs. This dissertation helps develop such understanding.

As was noted earlier, some RFID advocates argue that it is especially advantageous to be an early adopter of RFID, despite technical problems that limit the technology, including its reliability (Shister, 2005; Woods, 2005). Because of the inevitable problems that are present with almost all new technologies, another school of thought would argue that it is better to delay investment until the "bugs" have been worked out, perhaps using a "fast follower" strategy (Carr, 2004). Because of the experimental design used by this dissertation, it is possible to compare perfectly reliable bar coding versus less reliable RFID to identify situations where RFID's current advantages (e.g., instantaneous scan times) might offset its current shortcomings.

Section 1.1 has described some of the primary objectives and expected contributions from this research. Additional expected contributions are listed in section 3.5.

1.2 Experimental design and research methodology

As noted in section 1.1, several of the experimental design factors in this dissertation come from classic planning and control research (Wagner and Ragatz, 1994; Smunt, Buss, and Kropp, 1996; Litchfield and Narasimhan, 2000), in order to facilitate a familiar model baseline that could be used to compare the impact of RFID. Additionally, new RFID- and bar coding-related factors that have never before been seen in research were introduced. The multi-level factors are shown in Figure 1.

Multi-Level Factor	Level Code	Level Description
Transfer lot tracking mechanism	TM1	RFID (Instantaneous read)
	TM2	Fast deterministic bar code (read takes 4 seconds)
	TM3	Slow deterministic bar code (read takes 10 seconds)
	TM4	Fast stochastic bar code (read time follows a gamma distribution with a mean of 4 seconds)
	TM5	Slow stochastic bar code (read time follows a gamma distribution with a mean of 10 seconds)
Read batching	RB1	Each read of each transfer lot occurs immediately after process completion at each work center
	RB2	1 percent of reads of eligible transfer lots batched
	RB3	2.5 percent of reads of eligible transfer lots batched
Number of transfer lots	NTL1	2 transfer lots of size 50 units each
	NTL2	5 transfer lots of size 20 units each
	NTL3	10 transfer lots of size 10 units each
	NTL4	20 transfer lots of size 5 units each
	NTL5	50 transfer lots of size 2 units each
Setup / processing time ratio	SPR1	10:100 (setup time is ~ 9 percent of setup + processing time for all units in the job)
	SPR2	50:100 (setup time is ~ 33 percent of setup + processing time for all units in the job)
	SPR3	100:100 (setup is 50 percent of setup + processing time for all units in the job)
Secondary dispatching rule	SDR1	FCFS (first come, first served)
	SDR2	SPT (shortest processing time)
	SDR3	ODD (earliest operation due date)
Coefficient of variation (CV) of processing time between work centers in routing	CV1	.07 (87.5 – 112.5 seconds / unit)
	CV2	.29 (50 – 150 seconds / unit)
Due date tightness	K1	2.5 times the total work content
	K2	5 times the total work content

Figure 1. Multi-level factors for experimental design

The first factor in Figure 1 focuses on the fact that RFID technology provides instantaneous tracking. The technical process of bar coding is also very fast, but because line-of-sight is required, the product typically requires some sort of physical reorientation for appropriate visibility by the bar code scanner (Kärkkäinen, 2003). Studies have indicated that it can take 4-15 seconds on average for the scanning and labor associated with this orientation, even in relatively repetitive environments (Palmer, 1995; Barlow, 2005; Kinsella, 2005; Navistar, 2006; Sullivan, 2007; Gaukler and Hausman, under review). In less repetitive environments such as job shops, one might reasonably expect that it could take even longer for operators to stop what they are doing, scan the product, and then resume the rest of their processing. For example, Gaukler and Hausman (under review) performed two industrial studies and estimated scan times of 10-12 seconds on average, but asserted that the times could be substantially more if workers have to walk to the location of the object to be scanned. Although a few seconds per bar code read might not seem like much, Kärkkäinen and Holmström (2002) observed, “Handling efficiency is the basis on which item level supply chain management is built on. It can be achieved, when products are identified without a need to physically handle them,” as is the case with RFID technology.

Besides requiring more time for positioning and scanning, bar code labels are also subject to smudging and other damage for which RFID is less susceptible (e.g., because the tags can be stored inside of products) (Kärkkäinen, 2003; Angeles, 2005; Global Commerce Initiative and IBM, 2005). When a bar code label needs to be re-read and/or replaced, the tracking process can take much more than 10 seconds (Gaukler and Hausman, under review). In this case, the statistical distribution of the tracking process would have a long tail, as is possible with the gamma distribution. Perhaps worse than the time necessary to re-read and/or replace the label, the product may not even be scanned, which may result in process problems or traceability non-conformance that lead to sanctions from the government or customers. Bacheldor (2006d) described a company that applied bar code labels to totes (i.e., containers) used to hold parts. When the labels were new, the read rate was about 1 failure per 100 totes, but after half a year, the failure rate was *approximately 50 percent!*

Thus, the five levels seen in the table are used to reflect the time it takes for identifying a transfer lot when using:

- RFID technology is being used (instantaneous reads) (TM1)
- deterministically fast bar coding (four seconds per read) (TM2)
- deterministically slow bar coding (ten seconds per read) (TM3)
- stochastically fast bar coding (a gamma distribution with a mean read time of four seconds) (TM4)
- stochastically slow bar coding (a gamma distribution with a mean read time of ten seconds) (TM5).

Previous lot streaming research has not considered the time it takes to track products (i.e., this TM factor).

As will be described in more detail with the rest of the experimental design in Chapter 3, the read batching (RB) factor can be used to represent unreliable data collection, either because workers performing the bar code activity do not consistently record transfer lots as having completed processing at a work center (and thus downstream work centers will not know that material is available to be pulled), or because the RFID technology is relatively new and thus may not reliably identify the completion of a transfer lot that is ready to be pulled. Thus, the time spent for the data collection activity (the TM factor) is modeled independently from the reliability of the transfer lot tracking mechanism process (the RB factor). The value associated with the RB factor level indicates the probability that the read of an eligible transfer lot will be skipped at the time that processing is completed for it. Although the literature and interviews with industry managers provide examples of procedures that are not reliably followed by workers without some form of additional controls like RFID technology (Raman, DeHoratius, and Ton, 2001; Hill Jr., 2004; Tellkamp, Angerer, Fleisch, and Corsten, 2004; Collins, 2006e; Gaukler and Hausman, under review), the impact of different levels of data collection process conformance on flow times and tardiness has never been modeled.

The number of lot transfer lots (NTL) factor corresponds to the extent of lot streaming used. Because the use of more transfer lots is synonymous with more lot streaming and smaller lot sizes, the use of more transfer lots can also be thought of as the extent that the process is changed as a result of the enabling RFID technology. As was discussed earlier, compared to data collection alternatives such as bar coding (TM2-TM5), RFID technology (TM1) enables better traceability and control of the increased number of transfer lots (NTL) moving through the system. Thus, RFID facilitates process changes (higher NTL) that in turn are expected to contribute to improvements in mean flow time (MFT) and proportion of jobs tardy (PT). Although other process changes are certainly possible as a result of RFID (Hardgrave, Waller, and Miller, 2005), the focus on the process change of using high levels of lot streaming that are not practical with bar coding was expected to result in relatively clear differentiation between RFID and bar coding performance. Furthermore, given that much of the RFID literature has posited that process changes are necessary to achieve significant improvement when using RFID (Byrnes, 2004; Sliwa, 2005b), the use of the lot streaming factor (NTL) allows comparison between the possible improvement when using RFID but not changing the process (TM1 and NTL1) versus using RFID to make increasingly more substantial process changes (TM1 and NTL2-NTL5).

Although metrics for many dependent variables were collected for each of the experimental design treatments (see section 3.3), the primary dependent variables discussed in this dissertation are mean flow time (MFT), proportion of jobs tardy (PT), and number of material movements (MM). MFT can be considered both a measure of customer service (smaller MFT is equivalent to lower lead times for which customers have to wait), as well as a measure of inventory (by Little's Law, flow times and inventory levels are proportional). PT is another measure of customer service. Kher et al. (2000) is the only other research that has examined the impact of increased lot streaming on the number of material movements, but they examined a flow shop (and not a job shop as in this research), and they modeled pull material movements slightly differently (see section 3.1). No research has modeled the shop floor impact of RFID on MFT, PT, and MM.

Because of the complexity of the experimental design, simulation is used to generate the wide range of stochastic data. This is the methodology used in similar research (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000; Litchfield and Narasimhan, 2000) that provides the familiar baseline used to evaluate RFID's attractiveness for the various conditions and policies. To increase the statistical power associated with the analysis of the 2700 treatment conditions, common random number streams were used across each treatment (Law and Kelton, 2000; Banks, Carson II, Nelson, and Nicol, 2001; Kelton, Sadowski, and Sturrock, 2004). Because of the use of common random numbers, a repeated measures ANOVA was appropriate for comparing the treatment effects (Keppel, 1991; Hays, 1994; Law and Kelton, 2000; Banks et al., 2001). As Keppel (1991) indicated, with repeated measures (also known as within-subjects) designs, the treatment effects are represented by differences within a single group of subjects. Because some of the sources of variation have been isolated in the analysis to reflect differences within each subject, the error terms are different from, and ideally smaller than, completely randomized (also known as between-subjects) designs (Keppel, 1991). See section 3.6 for further methodological discussion.

1.3 Research Hypotheses

Previous related research (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000; Litchfield and Narasimhan, 2000) has been exploratory and did not formally state hypotheses. Instead, the lot streaming research using simulation has typically been meant to test the effect of the factors and their levels. This dissertation presents the less formal expected results sometimes seen in previously published lot streaming research, as well as more formal and statistically precise *alternative* hypotheses.

H1. The forms of bar coding with stochastic read times should show worse mean flow time (MFT) and proportion tardy (PT) performance than their deterministic bar coding counterparts. Stated more formally, TM4 should have numerically higher MFT and PT than TM2, and TM5 should have numerically higher MFT and PT than TM3, statistically significant at no more than $p<.10$ when performing pairwise comparisons. This would be congruent with the basic queuing and "factory physics" principles discussed in Hopp and Spearman (2001), that increasing variability degrades the performance of a manufacturing system. Lee and Whang (2005) noted that the cornerstone of Motorola's widely acclaimed Six Sigma program was to continuously reduce process variability, so a reduction in bar code read time variability could reasonably be expected to lead to improved MFT and PT performance.

H2. With increased transfer lots (NTL), mean flow time (MFT) and proportion of jobs tardy (PT) will improve when using RFID (with TM1). Stated more formally, with the tracking mechanism held constant at level TM1, increasing NTL should result in increasingly smaller MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. When *not* using RFID (when not using TM1), increased NTL will result in better MFT and PT performance at first, and then lead to worse performance. Stated more formally, when using TM2 - TM5, increasing NTL should result in increasingly smaller MFT and PT up to some switchover point, before further increasing NTL results in increasingly larger MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. This issue has not been previously researched, but is based on the idea that the time spent performing the bar code tracking activity for an increasing number of transfer lots will eventually offset any performance gains from using increased lot streaming.

H3. The improvement in mean flow time (MFT) and proportion of jobs tardy (PT) performance with increased lot streaming (higher NTL) should be lower when the setup / processing time ratio increases (when SPR increases). Stated more formally, an NTL*SPR interaction effect (statistically significant at no more than $p<.10$) is expected to be identified for MFT and PT. This is compatible with the data from Smunt et al. (1996).

H4. With the tracking mechanism held constant at RFID (TM1), increasing the amount of lot streaming (NTL) should result in increasingly numerous material movements (MM), statistically significant at no more than $p < .10$ when performing pairwise comparisons between adjacent NTL levels. Such findings for the job shop modeled in this dissertation would be compatible with the flow shop study by Kher et al. (2000).

H5. Mean flow time (MFT) and proportion of jobs tardy (PT) should increase (be worse) with more read batching (with greater RB). Stated more formally, increasing levels of RB should result in higher MFT and PT, statistically significant at no more than $p < .10$. This is because with increased read batching, it is more likely that a downstream work center will choose a different job type to process, and thus waste capacity on performing a new setup for that other job type.

H6. Mean flow time (MFT) should be best with the shortest processing (SPT) dispatching rule (SDR2). When due dates are tight (K1), then proportion of jobs tardy (PT) should be best for the SPT dispatching rule (SDR2). When due dates are loose (K2), then PT should be best for the earliest operation due date (ODD) dispatching rule (SDR3). Stated more formally, the SPT rule (SDR2) is expected to be statistically better (at no more than $p<.10$) than FCFS (SDR1) and ODD (SDR3) for MFT. An SDR*K interaction effect is expected to be identified for the proportion of jobs tardy (PT), with the SPT rule (SDR2) being statistically better (at no more than $p<.10$) with tight due dates (K1), and the ODD rule (SDR3) being statistically better (at no more than $p<.10$) for loose due dates (K2). This would be compatible with the findings of Baker (1984) and Jayamohan and Chandrasekharan (2000).

H7. Proportion of jobs tardy (PT) performance should be better when there is more slack allowance for due dates (K2). Stated more formally, the K2 due date multiplier factor level should result in smaller PT (statistically significant at no more than $p < .10$) compared to when the K1 factor level is used. This is based on the basic characteristics of the TWK due date rule that calculates later due dates when using a higher multiplier.

1.4 Layout of dissertation

Chapter 2 briefly reviews the relevant RFID and manufacturing literatures. Chapter 2 can be summarized by observing that with the exception of Gaukler and Hausman (under review) and Hou and Huang (2006), other research has not quantitatively compared RFID and bar coding. The research of Gaukler and Hausman (under review) was in the context of an assembly line, not a job shop, and Hou and Huang (2006) performed a relatively high-level study of a printing industry supply chain. Previous research has not examined the interaction effect of the time necessary for the data collection operation (e.g., the time to position and scan a bar code) with ever smaller lot sizes. Furthermore, previous research has not examined the performance impact of process non-conformance (e.g., read batching) during data collection. With the exception of Kher et al. (2000), previous research has not quantitatively examined the effect of smaller lot sizes on the increase in material movements. Kher et al. (2000) examined a flow shop (not a job shop as with this dissertation), did not explicitly contrast the material movement trade-off for various conditions and policies, and did not study all of the factors and levels used here.

Chapter 3 describes in detail the dissertation experimental design. Section 3.1 discusses each of the fixed factors, and each of the multi-level factors is presented in section 3.2. Section 3.3 lists the various dependent variable performance metrics. The hypotheses and the reasoning behind them are in section 3.4. Section 3.5 describes expected contributions of the research. Section 3.6 discusses methodological issues associated with the simulation and corresponding repeated measures ANOVA analysis.

Chapter 4 details the various steps used to verify and validate the simulation model. Section 4.1 discusses the code review of the simulation logic used to implement the experimental design. Section 4.2 describes the interactive verification tools that were specially developed beyond the core functionality present within the commercial Arena simulation package. Section 4.3 shows example log files that were specially designed and used to provide another means of systematically verifying that the simulation was implemented as intended. Section 4.4 describes how the interactive verification tools and log files were used for verification of each of the multi-level and fixed experimental design factors. To the extent that it is possible given the new factors used for this dissertation, section 4.5 compares pilot study results to previous related research as further evidence of the validity of the model. Section 4.6 discusses how the real-world performance of a major industrial company that already uses RFID was duplicated.

Chapter 5 presents and analyzes the results with a strong emphasis on using a scientific and statistical perspective, although concise managerial insights are also given. The chapter begins by reviewing the experimental design. Then, the results and analysis associated with each hypothesis are presented in sub-sections corresponding to each hypothesis, along with related follow-up research. For example, the discussion for Hypothesis 5 includes results that strictly relate to the original read batching (process reliability) hypothesis, but it also includes additional discussion that combines those results with those of earlier hypotheses. In this case, the combined results were used to help design a follow-up test to see if conditions where RFID was previously shown to be better than bar coding will lead to different results if the reliability of RFID is poor and the reliability of bar coding is perfect.

The conclusion in Chapter 6 summarizes the results from Chapter 5 and provides additional managerial discussion. Section 6.1 is divided into sub-sections that correspond to each of the hypotheses. Section 6.2 discusses the relation between different types of flexibility and lean production enabled by RFID. Section 6.3 describes future research opportunities.

CHAPTER 2

LITERATURE REVIEW

This chapter primarily reviews the academic RFID literature. As of early 2007, most RFID research has either been qualitative or not provided much supporting quantitative and operational details that would help in understanding how the results generalize (Gilmore and Fralick, 2005; Murphy-Hoye et al., 2005). Because of the operations focus of this dissertation, RFID literature that focuses primarily on issues related to security, privacy, or the underlying technical details is not covered by this review. Some discussion of the key literature related to the dissertation's lot streaming production model is also provided in this chapter, although the bulk of such material is given in Chapter 3 to help justify the experimental design.

2.1 RFID literature

Despite the lack of quantitative RFID research, numerous conceptual overviews and case studies of RFID applications, opportunities, and risks have been published in the academic literature (Srivastava, 2004; Borriello, 2005; Narsing, 2005; Barut, Brown, Freund, May, and Reinhart, 2006; Bean, 2006; Higgins and Cairney, 2006; Li and Visich, 2006; Markelevich and Bell, 2006; Roberts, 2006; Wu, Nystrom, Lin, and Yu, 2006;

Wyld, 2006). Illustrating that RFID has actually been used for many years, Ollivier (1995) described how RFID leads to major accuracy and efficiency improvements in material handling systems, even compared to other automation technologies such as photocells and limit switches. Kärkkäinen and Holmström (2002) discussed how RFID can enable handling efficiency, customization, and information sharing. This dissertation fills a research gap by quantitatively building on some of their early concepts. Kärkkäinen (2003) also described how bar coding "invariably requires manual handling in the supply chain," but RFID does not, and thus supports more efficient management and improved traceability through the supply chain. This dissertation quantitatively shows how RFID can offer benefits for manufacturers and supply chains that have high traceability requirements. McFarlane and Sheffi (2003) discussed how RFID can provide value at each stage of the supply chain, including within the manufacturing plant.

Lapide (2004) discussed how the better information from RFID might be used to improve forecasting. Rutner et al. (2004) particularly focused on the potential impact of RFID on retail supply chains. Sheffi (2004) discussed technologies that have historically been considered "disruptive" to analyze the future adoption and impact of RFID.

Angeles (2005) cited a variety of practitioner sources to provide an introduction to RFID, including several case examples and implementation guidelines. Asif and Mandviwalla (2005) provided a technical and business analysis of how RFID could help integrate the supply chain. Lai et al. (2005) used field interviews and panel discussion to identify the opportunities and challenges for RFID in China. From their conceptual analysis, they came to the conclusion that companies that were too cautious in their RFID adoption approach were at risk of losing market share, whereas early adopters of RFID can achieve significant long-term advantages. Murphy-Hoye et al. (2005) discuss pathways that companies use to adopt RFID, the need for quantitative analysis based on detailed process mapping of operations, and unexpected ways that RFID can redefine physical and logical supply chain systems. This dissertation builds on their conceptual insight that the automation provided by RFID can enable better material flows and mass customization. Prater, Frazier, and Reyes (2005) provided a conceptual framework of research areas that are of importance to the grocery industry. Yang and Jarvenpaa (2005) applied social theories related to trust and power to examine the adoption of RFID as a type of newly emerged interorganizational system (IOS) in contractual alliances.

Hassan and Chatterjee (2006) presented a taxonomy of RFID organized around usage, physical, frequency, and data dimensions. Using theories from the cognitive science, management, and political science literatures, Riggins and Slaughter (2006) examine the mental models used during RFID adoption. Curtin, Kauffman, and Riggins (2007) discuss how RFID technology can dramatically enhance an organization's capability to capture information about mobile entities, use information across a wide range of processes and organizations, and facilitate tying together different systems. The ability of RFID to trace work-in-process (a mobile entity) is a key feature of RFID that leads to the benefits that are quantitatively studied in this dissertation.

The RFID citations in the previous paragraphs were conceptual in nature or based on case studies. Far fewer quantitative RFID studies exist. Kang and Gershwin (2005) used simulation modeling to compare automatic identification technologies (such as RFID) that are assumed to have perfect inventory accuracy against alternatives such as safety stock that compensate for poor accuracy. They found that even without RFID, inventory inaccuracy can be effectively controlled if the stochastic behavior behind the inaccuracy is known. Thus, they concluded that RFID is not always an ideal investment, which is a conclusion similar to one developed by this dissertation; RFID is an investment that needs to be made strategically based on other contextual factors such as the operating conditions. Kohn, Brayman, and Littleton (2005) developed a framework that uses differential equations for real-time planning, scheduling, and control to respond to unexpected events in a manner that balances responsiveness and disruptions (e.g., system nervousness and instability).

Hou and Huang (2006) developed cost and benefit models for printing industry supply chains based on the time savings made possible by RFID and the cost of tags, hardware (e.g., readers), and labor. Larson et al. (2006) used data collected from RFID tags attached to shopping carts to develop better understanding of how customers actually move throughout supermarkets. Vijayaraman and Osyk (2006) surveyed manufacturers, distributors, logistics providers, and retail firms to analyze issues related to RFID adoption. Retailers generally expect to achieve a positive return on investment (ROI), but manufacturers do not. Using RFID to enable business process reengineering (BPR) was seen as a way to improve RFID's ROI.

Besides this dissertation, a few others also look at RFID. The dissertation of Gaukler (2005) consisted of a series of papers that look at costs and incentive issues in an implementation of RFID across the supply chain, examine the value of supply chain visibility, and analyze the benefits of RFID for an assembly line process. Tellkamp (2006) wrote his dissertation about the use of RFID in fast-moving consumer good (FMCG) supply chains. He used a combination of conceptual analysis, case-based research, and modeling of RFID's impact on the receiving process, inventory accuracy, and moving inventory more quickly from a retailer's storeroom to the sales floor. As part of the lead author's dissertation, Langer, Forman, Kekre, and Scheller-Wolf (2007) used a probit model with archival data from a third party logistics company to analyze how RFID impacts return center logistics.

2.2 Literature related to the production model

Woods (2005) suggested that it is better to use RFID with processes that are unpredictable, unstructured, or chaotic. So-called job shops are typically used as classic examples of such processes. Compared to flow shops, processes in job shops are more difficult to control and material is more difficult to track because of the diverse production along varying flows between work centers. Job shops have historically been associated with flexible production that can produce a large variety of products (Hayes and Wheelwright, 1984; Ward et al., 1998; Duray et al., 2000), but traded-off against higher cost (Boyer and Lewis, 2002). Being able to efficiently produce a wide variety of products to meet differing customer needs is an increasingly important manufacturing capability (Swink and Hegarty, 1998; Vokurka and O'Leary-Kelly, 2000; Das, 2001; Schmenner and Tatikonda, 2005). Thus, job shops are an essential area to study, and any opportunity to simultaneously improve along additional competitive priorities beyond flexibility is important in an era of the pressures of global competition.

Researchers such as Jacobs and Bragg (1988), Wagner and Ragatz (1994), and Smunt et al. (1996) have shown how lot streaming can improve performance in job shops by reducing tardiness and flow times (and thus reducing inventory costs in addition to lead times). As noted in the introductory chapter, lot streaming allows smaller "transfer lots" created from an initial job to move independently through a plant (Litchfield and Narasimhan, 2000). Although researchers have observed that creating relatively more transfer lots from a job improves performance along the aforementioned dimensions, traceability issues pose an impediment. With increased transfer lots comes increased likelihood that the exact history of products will not be accurately recorded, because of natural human limitations in our ability to reliably execute the tracking process and physically maintain transfer lot integrity (Kher et al., 2000), particularly in job shops (Litchfield and Narasimhan, 2000). With industry concerns about liability, quality, process improvement, and warranty costs, traceability is increasingly important and often covered under governmental and customer compliance mandates (Kher et al. 2000, Jacobson 2006). While bar-coding can help, it adds time to production processes and is reliant on human execution that is inherently imperfect. Thus, companies have to consider the trade-off between increases in performance associated with increased lot streaming versus increased non-value-adding time and traceability errors associated with bar coding.

This research posits that RFID removes a key barrier to moving to smaller transfer lots and better performance than previously possible, because RFID allows automatic tracking without being reliant on the limitations of human performance. Additional lot streaming references are cited in Chapter 3 to provide justification for the experimental design.

CHAPTER 3

EXPERIMENTAL DESIGN

This chapter presents the methodology for evaluating the conditions and policies that affect performance in a job shop that uses lot streaming with RFID or bar coding. A review of the lot streaming literature indicates that analytical approaches are sometimes used to research lot streaming for relatively simple conditions (Chang and Chiu, 2005), but simulation is generally used for more realistic models (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000; Litchfield and Narasimhan, 2000). Simulation allows experimental conditions to be defined and manipulated with much better control than is often possible if the experiment were to be actually performed in the real world, thus reducing the possibility that confounding factors will lead to misleading interpretation of results (Law and Kelton, 2000). Simulation also allows large quantities of data to be collected and analyzed for scenarios that may not be readily testable in real-world situations. Given the relatively low prevalence of RFID, this is an important consideration for researchers wanting to perform rigorous statistical analysis. Thus, simulation is the research methodology used to generate data for this dissertation.

The experimental design is grounded on prior lot streaming, RFID, and scheduling literature, as well as insights from working with an industrial partner. The following sub-sections define and discuss the fixed factors (3.1), multi-level factors (3.2), dependent variables (3.3), basic hypotheses (3.4), expected contributions (3.5), and methodological issues (3.6) related to the use of simulation for data generation and repeated measures ANOVA for statistical analysis.

3.1 Fixed factors

Figure 2 summarizes the fixed factors that are used to define the shop environment used by this dissertation, and the rest of this sub-section provides additional detail. It should be noted that while consideration was given to choosing multiple levels for some of these factors, the experimental design already had 2700 treatment combinations based on the multi-level factors discussed in section 3.2. Without developing a sound understanding of the model from a relatively simple baseline, future research would not have a solid footing to build on.

Fixed Factor	Factor Value
Process flow	Job shop with no recirculation
Job variety	Open shop (all jobs are unique)
Number of work centers	8 work centers
Number of operations per routing	Between 1 and 8
Process balance	Balanced processes
Processing time uncertainty	Actual processing time = Expected processing time
Estimated utilization	80%
Job interarrival time	Exponential distribution (mean set to achieve 80% utilization based on the setup/processing time ratio)
Job size	100 units
Primary dispatching rule	Repetitive lots
Material handling philosophy	Pull material movements
Material movement transfer speed	Instantaneous

Figure 2. Fixed factors for experimental design

Process flow

In a job shop, the material flow specified by the routing varies by each job type. In a flow shop, material always moves from work center to work center in the same sequence, regardless of job type.

Jacobs and Bragg (1988) and Wagner and Ragatz (1994) only considered job shops. Smunt et al. (1996) considered both job shops and flow shops. They found that the overall benefits of lot splitting were greater in flow shops than in job shops. Kher et al. (2000) only considered flow shops. Jacobs and Bragg (1988) modeled a job would never require processing in the same work center more than once (i.e., there was no chance of recirculation); Smunt et al. (1996) said they modeled their job shop after Jacobs and Bragg (1988). Wagner and Ragatz (1994) allowed a job to be processed at the same work center more than once, but the processing at the same work center could not be for concurrent operations.

The literature review of section 2.2 provides more justification for the job shop model used for this dissertation. A standard job shop configuration provides a familiar generalizable baseline. Job shops support a wide variety of products, and such flexibility is increasingly necessary in today's competitive marketplace. Without RFID, achieving traceability and control is more difficult in the jumbled material flow of job shops compared to the direct material flows used in flow shops. Furthermore, the trade-off of increased material movements against improvements in other performance metrics when using small lot sizes has not been quantitatively measured in a job shop. Similar to Jacobs and Bragg (1988) and Smunt et al. (1996), no job recirculation is allowed.

Job variety

In scheduling nomenclature, each job in an "open shop" is unique, whereas "closed shops" produce only a finite range of job types. A new setup is required when production begins on the transfer lot of a different job type than was previously made at a given work center. On the other hand, transfer lots of the same job type that are processed "back-to-back" at the same work center require no setup between them. Jacobs and Bragg (1988) and Smunt et al. (1996) assumed closed job shops with ten distinct job types. Wagner and Ragatz (1994) compared open job shops and closed job shops. In their closed job shop, there were eight distinct job types. They found that the benefit of lot splitting was somewhat smaller in a closed job shop compared to an open job shop.

This dissertation models an open job shop, in part because of concerns about the interpretability and generalizability of results from closed job shops due to the routings specifically modeled and the impact of their flows. As noted in section 2.2, modeling an open job shop also shows how RFID can improve efficiencies even in environments that simultaneously have requirements for high levels of production variety and traceability.

Number of work centers
and
Number of operations per routing

Jacobs and Bragg (1988) assumed that each job required between four and six operations that took place at any of ten work centers. Wagner and Ragatz (1994) modeled a shop with five machines. Upon arrival to the system, the first operation was randomly assigned to one of the machines; thereafter, each job had an equal chance of being assigned to one of the other machines or exiting the system. Jobs were limited to a maximum of 8 operations, which means that each job required 4.16 operations on average. Smunt et al. (1996) assumed that each job required five operations at any of ten work centers in their job shop.

This dissertation randomly generates the number of operations for the routing from a uniform distribution between one and eight, which means that the average job has 4.5 operations. There are eight work centers, approximately midway between the number used in the aforementioned research.

Process balance

As with Jacobs and Bragg (1988), Wagner and Ragatz (1994), and Smunt et al. (1996), balanced processes were used (the expected utilization was the same at each work center).

Processing time uncertainty

The actual processing time per unit will equal the expected processing time. As noted in section 3.2, there is known variation in the processing time for each job's routing operation. A stochastic per unit processing time is applied to all units within a job for a given routing operation, but varies from job to job and work center to work center. If modeling transport time and/or limited transporters that needed to be scheduled based on expected completion dates, having process time uncertainty would be more important. In light of the dissertation's goal of producing an easy to understand baseline that can be extended by future research, processing time uncertainty would just add confounding "noise" to the analysis.

Estimated utilization

Baker and Kanet (1983) examined government reports to conclude that most firms had utilizations that ranged from 80 to 90 percent. Jacobs and Bragg (1988) modeled a shop with a target utilization of 90 percent. Wagner and Ragatz (1994) modeled an expected utilization of 85 percent. Smunt et al. (1996) modeled target utilization scenarios of 57, 72, and 87 percent that led to actual utilization from between 60 to 95 percent. They concluded that increased lot splitting was more beneficial in environments with higher utilization. Kher et al. (2000) considered expected utilizations of 70 and 90 percent, and concluded that lot splitting offers the most benefit under high utilization levels.

Highly utilized shops require a high TWK due date parameter that would be inappropriate for low-utilized shops. Because a full-factorial experimental design was desired, a utilization of 80 percent was chosen that provides insights with different levels of the TWK parameter while still within the range used by previous lot streaming and empirical research.

The arrival rate of jobs is adjusted based to achieve the desired utilization in light of the setup and processing times. As noted in the below discussion for "Arrival rate of jobs", the treatments for bar coding will be based on the interarrival rate for the corresponding RFID treatment, but the expected utilization for those bar coding experimental design treatments can be computed as:

$$\frac{\left[\left(Expected\ Operation\ Time \times Units\ Per\ Job\right) + Setup\ Time + \left(Mean\ Scan\ Time \times \#\ of\ Transfer\ Lots\right)\right] \times Mean\ Number\ of\ Routing\ Operations}{Mean\ Inter-Arrival\ Time \times Number\ of\ Work\ Centers}$$

Job interarrival time

Jacobs and Bragg (1988) generated demand at the start of each period for the next period and released work to the shop based on a fixed order quantity rule. As is common in much of the scheduling literature, Wagner and Ragatz (1994) and Kher at al. (2000) modeled job interarrival times with an exponential distribution (i.e., the interarrival rate was modeled with a Poisson distribution). Smunt et al. (1996) used a gamma distribution with CV = 0.50, as well as a deterministic distribution. Their data indicated that lot streaming had more of a benefit when there was deterministic interarrival times compared to stochastic interarrival times.

It is arguably more appropriate to use a stochastic distribution than a deterministic distribution when modeling an open job shop that would be using less predictable and less regular production because of its make-to-order strategy. Based on the common research approach of using exponential interarrival times, this dissertation also uses that distribution. The distribution of job interarrival times is adjusted to approximately meet the desired utilization. The arrival rate was computed as

$$\frac{\left[\left(Mean\,Units\,Per\,Job \times Expected\,Operation\,Time\right) + Setup\,Time\right] \times Mean\,\#\,of\ \ Routing\,Operations}{Expected\,Utilization \times Number\,of\,Work\,Centers}$$

As can be seen by the above equation, the mean arrival time does not directly change based on the mean scan time (for each level of SPR, the same mean interarrival time was used regardless of the level for TM). The mean interarrival time was set based on an 80 percent utilization rate with instantaneous scanning, and then the same mean interarrival time was used for the other tracking method levels. The result is that the expected utilization when bar coding was used was slightly higher than 80 percent (e.g., 80.727% with TM=3 and NTL=3).

Job Size

Smunt et al. (1996) used jobs sized between 75 and 225 units to “represent typical lot sizes in a repetitive batch environment.” In their complex ANOVA with many factors and levels, they found that the main effect for job size made the smallest contribution to explanation of variance.

A deterministic original job size ("release batch") of 100 is used in this dissertation to allow the effects of the number of transfer lots and the setup/processing ratio to be seen without the additional "noise" of varying job quantity.

Primary dispatching rule

The primary dispatching rule is the dispatching rule that is first applied when choosing which transfer lot to process next at a work center. If no transfer lot meets the criteria of the primary dispatching rule, the secondary dispatching rule (SDR) will be used (see section 3.2).

Repetitive lots is the standard primary dispatching rule used with lot streaming (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000). It tries to minimize the number of setups by choosing transfer lots based on the job type that was just processed at a newly idle work center. It has good performance despite its simplicity. See "Material handling philosophy" below for more information.

Because of the success and popularity of the repetitive lots rule in past research, it is also used with this dissertation.

Material handling philosophy

Until Kher et al. (2000), lot streaming researchers (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996) generally assumed that when a transfer lot was completed at a work center, it would automatically be pushed to the next work center. Most researchers other than Kher et al. (2000) simply said that more material movements would result when using increased numbers of transfer lots (i.e., smaller lot sizes), but those other researchers did not actually attempt to measure or reduce the number of material movements.

With the pull material movement logic used in this dissertation, when a transfer lot completes at a work center, if the next work center in its routing is idle, it will automatically move to that next work center; otherwise, the transfer lot will remain in a queue immediately after the work center that just processed it.

When a transfer lot completes at a work center, the next transfer lot to be processed at that work center is chosen based on the following criteria:

1. Repetitive lots logic is used to see if there is a transfer lot ready to be processed at the work center that is the same job type as the transfer lot that was just processed at that work center. If so, that transfer lot will be used (regardless of any other dispatching criteria, such as the secondary dispatching rule).
2. If no transfer lots meet the repetitive lots criteria, a secondary dispatching rule is used to evaluate the various alternatives.

It is important to note that the queue immediately in front of the work center in question will be searched, as well as queues after other work centers that are holding completed transfer lots waiting to be pulled forward. If a transfer lot is pulled forward, other transfer lots in the same queue that are waiting to move to the same downstream work center will also be pulled forward as part of the same material movement, regardless of whether they are all the same job type. In this way, the pull logic should result in fewer material movements than the classic push logic. Note that moving all transfer lots from the upstream work center, even if there are multiple job types, is different from the pull approach used by Kher et al. (2000), who allowed only one job type to be pulled at a time. They noted in their conclusion that the approach used by this dissertation should allow for a larger reduction in material movements.

RFID-enabled pull material movements are already in place in several forms today. AM General, maker of Hummer sport utility vehicles, uses an RFID system to signal that material should be pulled to workstations in need of replenishment, thus supporting its lean initiative with a form of electronic kanban (Hill, 2004). Electronic kanban systems not only help avoid problems with traditional cards that can be lost, but provide visibility for the entire system instead of just adjacent production cells (Michel, 2006). MTU Aero Engines added RFID tags to kanban cards so that when workers place the cards in a “mailbox”, an RFID reader will automatically notify the ERP system that more parts should be pulled to the location specified on the kanban card (Collins, 2006c). DaimlerChrysler has added RFID to kanban cards in order to track whether parts are in supplying storage areas or are being used on the production line, thus providing real-time visibility that eliminates manually intensive and time-consuming inventory counts (Collins, 2006b). Boeing tracks some of its parts totes using RFID (Hannon, 2005), and DHL has helped develop a “smart box” that uses an embedded RFID reader to track when tagged items are put in or taken out of the container (Wessel, 2007). Menges (2006) noted that GE Aviation uses RFID to track work in process (WIP), with an end goal of creating pull triggers based on RFID reads to enhance inventory management and production scheduling. By keeping track of the current inventory in a “smart box” tote, a pull signal could be generated in advance of the box actually being emptied, based on current production and kanban tote transit times.

Material movement transfer speed

The lot streaming literature review of Chang and Chiu (2005) does not cite any multi-product simulation research that has modeled transfer capacity and transfer time between work centers, perhaps because of the complexity and difficulty in developing generalizable parameters. This dissertation also assumes transporters with infinite capacity and instantaneous transfer speeds. Future work may want to model the number of transporters to move material from work center, the capacity of each, their speed, the distance between work centers, and the time it takes to load and unload.

3.2. Multi-level factors

The multi-level factor experimental design used for the simulation model is seen in Figure 3, and each of the factors is discussed in sequence over the following pages. Relevant use of similar factors in prior research is discussed in this sub-section. Basic hypotheses about the factor levels and their interactions are discussed section 3.4. The statistical aspects of the experimental design will be discussed in more detail in section 3.6, although it is noted here that there are a total of 2700 (5x3x5x3x3x2x2) treatment combinations.

Multi-Level Factor	Level Code	Level Description
Transfer lot tracking mechanism	TM1	RFID (Instantaneous read)
	TM2	Fast deterministic bar code (read takes 4 seconds)
	TM3	Slow deterministic bar code (read takes 10 seconds)
	TM4	Fast stochastic bar code (read time follows a gamma distribution with a mean of 4 seconds)
	TM5	Slow stochastic bar code (read time follows a gamma distribution with a mean of 10 seconds)
Read batching	RB1	Each read of each transfer lot occurs immediately after process completion at each work center
	RB2	1 percent of reads of transfer lots batched
	RB3	2.5 percent of reads of transfer lots batched
Number of transfer lots	NTL1	2 transfer lots of size 50 units each
	NTL2	5 transfer lots of size 20 units each
	NTL3	10 transfer lots of size 10 units each
	NTL4	20 transfer lots of size 5 units each
	NTL5	50 transfer lots of size 2 units each
Setup / processing time ratio	SPR1	10:100 (setup time is ~ 9 percent of setup + processing time for all units in the job)
	SPR2	50:100 (setup time is ~ 33 percent of setup + processing time for all units in the job)
	SPR3	100:100 (setup is 50 percent of setup + processing time for all units in the job)
Secondary dispatching rule	SDR1	FCFS (first come, first served)
	SDR2	SPT (shortest processing time)
	SDR3	ODD (earliest operation due date)
Coefficient of variation (CV) of processing time between work centers in routing	CV1	.07 (87.5 – 112.5 seconds / unit)
	CV2	.29 (50 – 150 seconds / unit)
Due date tightness	K1	2.5 times the total work content
	K2	5 times the total work content

Figure 3. Multi-level factors for experimental design

The setup/processing time ratio (SPR) and coefficient of variation of processing time between work centers (CV) factors can be thought of as operating conditions, and the secondary dispatching rule (SDR) and due date tightness parameter (K) can be thought of as operating policies. The terms “operating conditions and policies” were used by Kher et al. (2000), who called for more varieties of conditions and policies to be included as model factors in related future lot streaming research (as noted in this chapter, this dissertation accomplishes that). An “operating condition” is a characteristic of the circumstances under which a manufacturer operates (e.g., because of its chosen product lines and processes), whereas as an “operating policy” is a decision rule used by the manufacturer. The term “operating condition” has sometimes been called an “operating environment” or “environmental characteristic” (Jacobs and Bragg, 1988; Smunt et al., 1996; Litchfield and Narasimhan, 2000), but based on early reviewer feedback, the use of the word “environment” will be minimized to reduce the potential for confusion with high-level, strategic connotations related to competition, customer characteristics, etc. (Anand and Ward, 2004). By comparing current operating conditions to the conditions shown to be appropriate for RFID use, companies can make better decisions about whether to invest in RFID or use a less expensive and complex data collection alternative. Similarly, companies that choose to use RFID will want to know if there are operating policies that can be used to maximize the value of their technology.

Transfer lot tracking method (TM)

Customer and government traceability compliance mandates are increasingly specifying that process information be reliably available in the event of recalls and related liability issues (Petroff and Hill, 1991; Steele, 1995; Kher et al., 2000; Chappell et al., 2003; Bacheldor, 2006a; Barlow, 2006; Collins, 2006a; Jacobson, 2006). Not all of the units in a job need to be tracked. In principle, a set of units can be assigned a common lot number, and as long as physical lot integrity is maintained (e.g., units move between work centers together and the units are processed sequentially without intermixing with other lots), only the lot needs to be tracked. Information about a given unit can be obtained by cross-referencing to the information stored about its associated lot.

RFID provides instantaneous tracking. The technical process of bar coding is very fast, but some have estimated that there is typically a one- to four-second lag for a successful read (Kinsella, 2005). Furthermore, because line-of-sight is required, the product typically requires some sort of physical reorientation for appropriate visibility by the bar code scanner (Kärkkäinen, 2003). Studies have indicated that it can take 4-15 seconds on average for the scanning and labor associated with this orientation, even in relatively repetitive environments (Palmer, 1995; Barlow, 2005; Kinsella, 2005; Navistar, 2006; Sullivan, 2007; Gaukler and Hausman, under review). In less repetitive environments such as job shops, one might reasonably expect that it could take even longer for operators to stop what they are doing, scan the product, and then resume the rest of their processing. For example, Gaukler and Hausman (under review) performed two industrial studies and estimated scan times of 10-12 seconds on average, but asserted that the times could be substantially more if workers have to walk to the location of the object to be scanned. Although a few seconds per bar code read might not seem like much, Kärkkäinen and Holmström (2002) observed, "Handling efficiency is the basis on which item level supply chain management is built on. It can be achieved, when products are identified without a need to physically handle them," as is the case with RFID. For example, one satellite equipment center consciously chose to use RFID instead of bar coding for its tracking of 4000 serialized configuration-controlled parts, noting that the necessary inventory control work when moving dozens of parts drawers was “a big deal” before they chose to use RFID (O'Connor, 2006b). One process that used to take the equipment center two hours can now be performed in less than five minutes. Similarly, Bacheldor (2006c) notes that after a Toshiba plant switched to RFID from bar coding, the time spent to process laptops through a warehouse was cut by 90 percent.

Besides requiring more time for positioning and scanning, bar code labels are also subject to smudging and other damage for which RFID is less susceptible (e.g., because the tags can be stored inside of products) (Kärkkäinen, 2003; Angeles, 2005; Global Commerce Initiative and IBM, 2005). When a bar code label needs to be re-read and/or replaced, the tracking process can take much more than 10 seconds (Gaukler and Hausman, under review). In this case, the statistical distribution of the tracking process would have a long tail, as is possible with the gamma distribution. Perhaps worse than the time necessary to re-read and/or replace the label, the product may not even be scanned, which may result in process problems or traceability non-conformance that lead to sanctions from the government or customers. Bacheldor (2006d) described a company that applied bar code labels to totes (i.e., containers) used to hold parts. When new, the read rate was about 1 failure per 100 totes, but after half a year, the failure rate was *approximately 50 percent!*

Thus, the five levels seen in the table are used to reflect the time it takes for identifying a transfer lot when using:

- RFID is being used (essentially instantaneous)
- deterministically fast bar coding (four seconds per scan)
- deterministically slow bar coding (ten seconds per scan)
- stochastically fast bar coding (a gamma distribution with a mean scan time of four seconds)
- stochastically slow bar coding (a gamma distribution with a mean scan time of ten seconds).

Previous lot streaming research has not considered the time it takes to track products (i.e., this TM factor).

It should be noted that in this simulation model, tracking products with bar codes is performed by the work center operator, and thus the work center cannot be utilized while products are being scanned. Each transfer lot is scanned when all units of the transfer lot have been processed at a work center. This is necessary to signal to downstream work centers that the transfer lot is ready to be pulled. The actual scanning of the transfer lot might be accomplished by scanning a tote used to hold the parts associated with the transfer lot.

When RFID is used, several approaches are possible to achieve instantaneous reads. Each tote could have an RFID reader that reads tagged parts as each is placed into the tote. When the last unit for the transfer lot has been placed in the tote, the system would know the transfer lot is ready to be pulled. Alternatively, each tote could have an RFID tag. When a transfer lot is complete and the tagged tote is moved away from the immediate proximity of the processing area, an RFID reader would immediately sense it and know it is ready for processing. Yet another option is that an RFID tag on the tote could act as a "call button", similar to the approach used by workers at AM General's Hummer plant to trigger the replenishment of specific parts and quantities to the assembly line (Hill Jr., 2004).

A key research question is the extent of the performance penalty associated with longer bar code read times and the interaction with other factors such as the number of transfer lots (NTL). Also of interest is the question of how much the variability of the stochastic bar code scanning processes (TM4 and TM5) will affect performance.

Read batching (RB)

Both the literature and interviews with industry managers provide examples of procedures that are not reliably followed by workers without some form of additional controls like RFID (Hill Jr., 2004; Tellkamp et al., 2004; Collins, 2006e; Gaukler and Hausman, under review). One manufacturing executive said, "…if human beings are involved, problems are going to happen" that reduce the effectiveness of the tracking process when using methods such as bar coding (SupplyChainDigest, 2006). Similarly, another executive noted (Barlow, 2006) that fast-paced environments that rely on people to scan bar codes are "prone to a high amount of error." Among the common practices with poor execution that Raman et al. (2001) discuss is when a cashier scans a single product container label multiple times instead of individually scanning containers that are the same price, but actually different. If someone bought five raspberry and five blueberry yogurts, but the cashier only scans a raspberry yogurt container ten times, the store's inventory system will not have an accurate count of each kind of yogurt, and stockouts may occur. Greengard (2004) writes, “Many companies monitor the movement of pallets, cartons and individual products by having employees scan bar codes at various stages of the production process, but that solution is labor-intensive and prone to errors.” RFID tracking would reduce the need for human discipline to adhere to the proper execution of the process. Similarly, Hill (2004) and Gaukler and Hausman (under review) provide examples of how RFID can be used with error-proofing mechanisms such as verifying that the proper components have been installed.

Based on the previous examples, it is not hard to imagine workers periodically batching the bar code reading of an accumulated set of transfer lots. They may do it because of carelessness, laziness, or perceived local efficiencies, similar to the above example of the cashier reading a single yogurt container ten times. A batching effect could also result if the read of a transfer batch is missed. For example, it was noted earlier that Bacheldor (2006d) discussed a real-world environment where a bar code label might only be readable fifty percent of the time. Lahiri (2006) stated that his experience with consulting clients that have automated systems in production environments has shown bar coding accuracy rates “typically in the 90 percent range or higher” and that “read accuracy in the range of 90 percent is common,” despite the fact that other studies have shown that bar coding is theoretically capable of much higher read rates. Barlas (2004) observed that feedback from bar code readers can be difficult to hear in some noisy manufacturing environments, so a worker may not realize that their intended read was unsuccessful. In the simulation model, the effect of a missed bar code read would be that a transfer lot would not be pulled until another transfer lot of the same job type was read and a material mover came to pull all ready transfer lots. While the delay until the completion of the next transfer lot for that job might be small, the resulting impact on overall material flows and associated capacity utilization might be larger.

Because a full factorial experimental design is used, the system will simulate read batching even when RFID tracking is also being used (with level TM1, when the transfer lots are being read instantaneously). Although some might think of RFID as a configuration of factor values that reflect a variety of its benefits (e.g., with TM1 and RB1, reflecting instantaneous reads and perfect reliability), there is also value in distinguishing between the time it takes to scan an identifier (TM) and the probability of read batching (RB). For example, the configuration of TM1 and RB3 might reflect a situation where RFID is being used (and thus there are instantaneous reads), but the RFID technology is relatively new and unreliable. Imperfect read rates are not uncommon, and the metal equipment and material seen in industrial environments can be especially problematic (Shister, 2005; Woods, 2005; Hoffman, 2006; Lahiri, 2006). Interesting insights should be possible by differentiating between read speeds (with TM) and data collection process conformance (with RB). For example, how does RFID with poor reliability compare to bar coding with high reliability?

The value associated with the RB factor level indicates the probability that the read of a transfer lot will be skipped at the time that processing is completed for it. This dissertation wanted to take a conservative look at the relative benefit of RFID, so read batching can only happen when the transfer batch that is being completed has another transfer batch of the same job type at the same work center that is also waiting to be processed. This captures the idea that an undisciplined worker might batch the bar code read of a transfer lot if there are other transfer lots of the same job type already waiting to be processed at the work center, but reads are less likely to be skipped when the last transfer lot for a job type has been processed and a new job type must be set up. Because of the way that read batching has been implemented, the actual percent of read batching performed will be somewhat less than that indicated by the nominal factor level value, particularly when there are few transfer lots per job.

Because the pull process only considers pulling transfer lots that have been recorded as being completed, it is expected that the batching of reads may result in inefficient pulling. For example, the repetitive lots logic (see the discussion of the primary dispatching rule in section 3.1) might be unnecessarily interrupted because the system incorrectly thinks an upstream transfer lot has not been completed. In such a situation, extra setups will be incurred if a work center then begins production of a different job type, which will in turn hurt performance as capacity is used inefficiently and flows are disrupted.

Number of transfer lots (NTL)

Trebilcock (2006) cited the research of ARC Advisory Group when he reported that manufacturers are particularly interested in using RFID for tracking work-in-process and using RFID for process improvement. The better tracking of RFID enables the process improvement of using smaller lot sizes, even in environments with traceability mandates that require high reliability. The probability of not adequately meeting traceability requirements increases with increased transfer lots, because there are inherently more opportunities for tracking and identification to be missed or improperly performed, especially with the complexity of more batches moving through the shop (Kher et al., 2000; Litchfield and Narasimhan, 2000). Even moderate levels of lot streaming might be unadvisable in environments that use bar coding if the risk of customer or government sanctions is high, or if liabilities or recall costs increase because traceability capabilities to identify the minimum scope of defective parts are insufficient due to the limitations of bar coding.

In contrast, automated tracking technologies such as RFID facilitate much-heralded production processes such as lean manufacturing with a batch size of one, mass customization, and continuous flow (Dighero, Kellso, Merizon, Murphy, and Tyo, 2005; Murphy-Hoye et al., 2005). Citing a recent report from research firm Frost & Sullivan, Neil (2006) noted that automotive, aerospace, and industrial products are three manufacturing sectors expected to see value from RFID over the next few years, leading to RFID growth in those areas from $71.3 million in 2005 to $225.7 million in 2007. The first two sectors are particularly well-known for their high-traceability requirements, and the latter two sectors are particularly well-known for their wide variety of production requirements that lead to the use of jumbled flows associated with job shops.

Because the use of more transfer lots is synonymous with more lot streaming and smaller lot sizes, the use of more transfer lots can also be thought of as the extent of process changes. Although other process changes are certainly possible as a result of RFID (Hardgrave et al., 2005), the dissertation's focus on the process change of using high levels of lot streaming that are not practical with bar coding was expected to result in relatively clear differentiation between RFID and bar coding performance. Furthermore, given that much of the RFID literature has posited that process changes are necessary to achieve significant improvement when using RFID (Byrnes, 2004; Murphy-Hoye et al., 2005; Sliwa, 2005b), the use of the lot streaming factor (NTL) allows comparison between the possible improvement when using RFID but not changing the process (TM1 and NTL1) versus using RFID to make increasingly more substantial process changes (TM1 and NTL2-NTL5). The former can be thought of as using RFID simply as a bar code replacement, whereas the latter case can be thought of as using RFID's enabling functionality for business process reengineering (BPR).

The effect of the number of transfer lots has been examined in past studies, but as will be discussed later, this dissertation extends earlier research. Although Jacobs and Bragg (1988) considered a range of job sizes (100, 120, 130, 140, 150, 200, 250, and 300 units), they only considered transfer batch sizes of 10 and 50 units (along with no lot streaming). Furthermore, they only used the SPT (shortest processing time) rule with transfer batches of size 10, they did not use the ODD (operation due date) rule at all, they modeled a closed job shop (not an open job shop), and the key performance measures were related to flow time (and not material movements or tardiness). Thus, it was difficult to get an exact sense of how the various performance improvements experienced diminishing returns with increasing use of lot streaming and how other lot streaming rules that might be used in an open job shop would affect performance.

For their "preliminary experiment" in an open job shop, Wagner and Ragatz (1994) considered transfer batch sizes of 10, 25, and 50 units (along with no lot streaming) for jobs that ranged in size from 50 to 700 units. While this allows for more insight into the diminishing returns from increased use of transfer lots, their preliminary experiment unfortunately only used the FCFS (first come, first served) rule, which they later showed in their "primary experiment" to have far worse performance than the earliest due date by job (EDD) and SPT rules. Conceivably, the EDD and SPT rules could have had an interaction effect with the number of transfer lots, but this is unknown because their primary experiment only used one level of transfer batches (50 units). Although they considered mean tardiness in addition to the flow time and flow ratio (the flow time divided by the total work content), they did not consider the proportion tardy.

Among the environments considered by Smunt et al. (1996) was a closed job shop similar to that used by Jacobs and Bragg (1988). They considered transfer batches (of unspecified size) based on 0, 2, 4, 8, 16, 32, and 64 splits of an original job of size 75 units. While this allowed graphs to be produced showing the diminishing returns from an increasing number of transfer lots, they only considered the FCFS rule and the mean flow time. Furthermore, they only used the relatively high setup/processing ratio of 1.00. With a ratio this high, it is relatively unlikely that a transfer lot that moves to a downstream work center will complete a setup and processing before an upstream work center finishes processing the remaining transfer lots in the job, which would lead to separation in the flow of the transfer lots and wasted time on extra setups. Their conclusions about the effects of the number of transfer lots are arguably not generalizable to environments with a lower SPR ratio.

Kher et al. (2000) considered splitting jobs of size 60-240 units with two, four, or eight splits, along with not using any lot streaming. Although they considered several performance metrics, they only used the FCFS rule and only studied a flow shop.

Based on past research, it is expected that increased use of lot streaming (higher NTL) will result in improved performance (albeit with diminishing returns) when no time is required to track the transfer lots (when using TM1). Hopp and Spearman (2001) explore this from a theoretical standpoint when they observe that increasing variability degrades the performance of a production system, and maximum variability can occur when moving product in large batches, even when process times are constant. This dissertation starts from a baseline of 2 transfer lots of 50 units in order to use valuable computer simulation time recording the diminishing returns at the other extreme (50 transfer lots of 2 units). The use of five levels for this factor allows the analysis to show if there is a "sweet spot" of the number of transfer lots to achieve a certain level of performance at the expense of material movements. Furthermore, there should be additional insights from the interaction of the read time associated with the tracking mechanism and the number of transfer lots employed. For example, performance may actually get worse when using bar coding with increased transfer lots if the diminishing performance with extreme lot streaming is more than offset by the time it takes to perform the tracking activity. Compared to earlier research, this dissertation considers more dispatching rules and performance metrics and focuses on an open job shop.

Setup/processing time ratio (SPR)

This is the time for a single setup divided by the total processing time (excluding setup and scan time) for all units of the job. There has been some speculation in earlier research that long setup times would decrease performance (Smunt et al., 1996), because as transfer lots get separated, multiple time-consuming setups could theoretically be incurred, even with the repetitive lots logic. A related implication is that the expected setup/processing time (SPR) ratio could be significantly different than the actual SPR ratio if the actual number of setups is drastically increased due to the use of lot streaming, the separation of transfer lots, and switching back and forth between setups due to the non-smooth flow of different job types into a work center.

Jacobs and Bragg (1988) used SPR ratios of between 16.6 and 38.8 percent. Their different ratios resulted from the way they allocated capacity based on the job size. Across the various runs they examined, the total runtime was fixed at 72 percent of the total capacity, but the capacity allocated for setups would fluctuate based on the number of setups that were required given varying fixed order quantities (FOQs). For example, when using an FOQ of 200, the SPR ratio was 25 percent, because 18 percent of the capacity was used for setups, and 72 percent was used for processing (not including setup time). When using an FOQ of 300, fewer setups were expected, so the expected capacity to be utilized for setups was approximately 12 percent, and 12 divided by 72 (the amount fixed for the runtime) results in an SPR ratio 16.6 of percent. When 28 percent of the capacity was used for setups, the SPR ratio would be 28/72=38.8 percent. Unfortunately, they did not directly discuss the effect of the different SPR ratios.

Wagner and Ragatz (1994) considered SPR ratios of 10, 20, 30, and 100 percent. They found that longer setup times do not "greatly" reduce the benefits from increased lot streaming. As noted earlier, though, for the portion of their paper that included SPR ratios, they only used the FCFS rule and did not record the proportion tardy.

Smunt et al. (1996) used the relatively high setup/processing ratio of 100 percent for the portion of their paper where they examined the effect of varying numbers of transfer lots, and they only considered the FCFS rule and the mean flow time. When simply comparing no lot streaming to the use of three equally sized transfer lots, their data indicated that lot streaming in their closed job shop with stochastic interarrival times offered greater benefits with lower SPR ratios (this conclusion was not specifically mentioned by them, but is based on information from their tables). For example, when the utilization was 72 percent, the use of lot streaming resulted in a reduction of flow time of approximately 37.3 percent when the SPR ratio was .1, but lot streaming resulted in a reduction of only 17.1 percent when the SPR ratio was 1.5.

Kher et al. (2000) considered SPR ratios of 25, 50, and 100 percent for their study of lot streaming in a flow shop using the FCFS rule. They concluded that lot streaming offers the most benefit for environments with high SPR ratios.

Because previous research did not consider the effects of the SPR ratio in an open job shop with the SPR and ODD dispatching rules, and because there are conflicting results about whether lot streaming is more beneficial with lower or higher SPR ratios, this dissertation includes factor levels of 10, 50, and 100 percent.

Secondary dispatching rules (SDR)

The second dispatching rule is applied when the repetitive lots logic (the primary dispatching rule) cannot find another transfer lot that is ready to be processed at a given work center that is the same job type as the transfer lot that just completed processing at that work center. In other words, the secondary dispatching rule is used when the primary dispatching rule (which is always repetitive lots) cannot find any transfer lots to process that meet its criteria for minimizing setups. See the discussion in section 3.1 for more information about the primary dispatching rule.

Jacobs and Bragg (1988) used both the FCFS (first come, first served) and SPT (shortest processing time) rules. According to their tables, the SPT rule performed better than FCFS for mean flow time when the release batch job size was 130-300 units, but performed worse when the job size was 100-110 units.

Wagner and Ragatz (1994) found that the SPT rule was always better than the FCFS rule for the flow ratio and flow time measures when using lot streaming in an open job shop. The EDD (earliest due date by job) rule was either better than, or statistically equivalent with, the SPT rule for flow ratio, and had mixed results for the flow time measure compared to SPT, but was always better than FCFS. For tardiness performance, the EDD rule was clearly the best, followed by FCFS, and then SPT. In contrast, Smunt et al. (1996) only considered the FCFS and SPT rules, only measured flow time, and used a closed shop. They found that flow times actually increased in job shops when the SPT rule was used (instead of FCFS), particularly for utilizations at least 72 percent. Their suspicion for the different results was that Wagner and Ragatz (1994) used an open job shop, or that Wagner and Ragatz (1994) perhaps allowed a wider range of task times. The former explanation is possible, but the latter is less plausible, because Wagner and Ragatz (1994) used a CV of 0.14, whereas Smunt et al. (1996) used a CV of 0.50 for their comparison of dispatching rules.

As noted above, earlier lot streaming research primarily focused on the FCFS rule, and to a lesser extent, the SPT rule. Those rules are also used here in the dissertation because 1) the prior research showed contrary results without clear resolution when comparing the relative benefit of each rule, 2) the rules had been applied in environments other than used for this dissertation, and 3) these relatively simple rules make a convenient baseline for future research of more complex rules.

Baker (1984) found that dispatching rules that are operation-oriented (such as the operation due date rule, ODD) perform better than rules that are job-oriented (such as EDD). In light of the fact that Wagner and Ragatz (1994) found that EDD performs as well as SPT and much better than FCFS, this dissertation examines how ODD compares to those rules. It is believed that this is the first time that ODD (or any other operation-oriented rule) has been used in a lot-streaming context.

It should be noted that when the SPT rule is used, the decision is made based on the shortest processing time *per unit*. As Wagner and Ragatz (1994) noted, there are multiple interpretations for the SPT rule when lot streaming is being used (they used the processing time of the entire job and not the per unit processing time, transfer lot processing time, or processing time of all transfer lots upstream for a given job type, which are also plausible interpretations for the SPT rule). Because all jobs are the same size and each job has the same number of transfer lots for a given treatment condition, the interpretation of per unit processing time is compatible with the basic SPT philosophy, prior research, and goal of this dissertation to develop relatively simple baselines for future research.

Although differences in performance are expected for the different dispatching rules (as discussed in the basic hypotheses of section 3.4), there is not any obvious reason to believe that there will be any interaction effect with the factors that relate to RFID. This is because those factors relate more to the increased tracking rate (TM), process conformance (RB), and support for using more transfer lots (NTL) that are associated with RFID. If there was processing time uncertainty, it is conceivable that a more complex dispatching rule that took advantage of the better information from an RFID system that was being used to track the progress of every unit would show an interaction effect (much greater performance with RFID use than without).

Coefficient of variation (CV) of processing time between work centers in routing

Jacobs and Bragg (1988) stated that actual run times averaged .0576 hours (207 seconds) per unit and ranged between .0458 and .0782 hours for all operations at all machines, but it is not clear what distribution was used to generate the run times. Without knowledge of the distribution, an accurate coefficient of variation (CV) cannot be calculated.

Wagner and Ragatz (1994) wrote, “Kropp et al. (1988) suggested that processing time variability was a critical factor to consider in determining whether lot splitting was beneficial.” For each job at each work center, Wagner and Ragatz (1994) applied a uniform distribution to determine the per unit processing time. For a given job at a given work center, all units had the same per unit processing time of 30-50 seconds, which means the CV was ~ .14 on a per unit basis. They wrote, “This is a rather severe test of the lot splitting mechanism, since the difference in processing time between successive operations can be considerable, and transfer batches of a job will tend to separate when a high processing time operation is followed by one with a low processing time.”

For the portion of their study that examined the effect of increasing number of transfer lots, Smunt et al. (1996) used a gamma distribution with CV’s of .01, .5, and 1.0 based on different levels of mean operation task times between .0456 - .0696 hours (164 – 251 seconds). They wrote, “Based on empirical evidence (e.g., (Dudley, 1963)), CV=0.50 is probably the closest to actual operation task times. Nevertheless, there are situations in which a high CV might be appropriate: unreliable machines with many machine breakdowns, excessive amounts of rework, etc.” Reading Dudley (1963), it is not explicitly clear if conclusions about the coefficient of variation should be based *per unit* or *per lot*; based on basic statistics and the central limit theorem, it seems like the distribution per unit might be highly skewed and variable, but the lot distribution should be more normal and less variable because of the aggregation of the per unit processing times. It also is not clear if the gamma distribution of Smunt et al. (1996) was applied to directly determine the distribution of processing times for each transfer lot, or if the distribution was individually applied to each unit within a transfer lot and then aggregated to produce a transfer lot processing time. Smunt et al. (1996) concluded that increased lot streaming was more beneficial with higher levels of the CV.

Kher et al. (2000) wrote that “processing times were generated using truncated normal distribution with a coefficient of variation (CV) of 10%”. It is not clear if this is the processing time distribution for each transfer lot or for each unit, and they do not indicate what the mean processing time is.

This dissertation uses a uniform distribution to generate per unit processing times. When the range is 87.5 – 112.5 seconds per unit, the CV is ~.07, half the CV used by Wagner and Ragatz (1994). When the range is 50-100 seconds per unit, the CV is ~.29, twice the CV of Wagner and Ragatz, but still half of what Smunt et al. (1996) feel is commonly observed in practice. At a given work center, the per unit processing time for a job type is applied to all units within the transfer lot, which makes the CV for the processing time of the transfer lot somewhat less than the CV for the processing time per unit. Rather than apply the same per unit processing time to all units, it would be possible to generate a unique processing time for each unit, but this would make the simulation runtime performance far worse, thus preventing the complex analyses of the various factors used by this dissertation.

Due date tightness (K)

In his general scheduling (non-lot streaming-specific) research, Baker (1984) found strong evidence that due dates should be based on work content, and that the total work (TWK) rule was typically the best of the due date setting rules. The K parameter for the TWK rule represents the multiple of the total work content that is used to compute each due date, and thus defines the due date tightness (Baker and Kanet, 1983). Specifically, the due date d_{ij} for operation i of job j can be defined as follows based on the total operation time (setup plus processing plus scan time) p_{ij} multiplied by the due date tightness K and added to the previous operation's due date $d_{i-1,j}$:

$$d_{ij} = d_{i-1,j} + K \times p_{ij}$$

Baker (1984) found that the effectiveness of dispatching rules can be affected by the due date tightness, producing what he called a "crossover effect." In particular, he found that SPT is relatively effective when due dates are very tight but not so when due dates are loose.

Baker and Kanet (1983) stated that for firms operating at utilizations of 80 percent, it is appropriate to assume that they would use K parameters somewhat less than 10. For their study of a basic job shop without lot streaming (that would presumably require higher K values to achieve satisfactory performance compared to shops that use lot streaming), they chose K values of 2.5, 5, 7.5, and 10.

Jacobs and Bragg (1988) and Smunt et al. (1996) did not consider due date performance measures, and thus did not use any due date rules. When comparing the SPT, FCFS, and EDD dispatching rules, Wagner and Ragatz (1994) used K values of 4, 6, and 8. When examining the effect of increasing the amount of lot streaming (increasing the number of transfer lots), they used a K value of 6. Kher et al. (2000) used a K value of 6 in their study of flow shops.

Based on the previous research, due dates for each operation (and thus the job) are set with the TWK rule in this dissertation. The total work content is based on the number of units and the setup, processing, and scan times at each work station. Regardless of the number of transfer lots, one setup is assumed per operation per job because of the repetitive lots logic used. The scan time is used to include time for each of the steps when a scan takes place, based on the number of transfer lots per job. Based on pilot runs, using K=2.5 would result in a proportion tardy of 30-50 percent, and K=5 would result in a proportion tardy of 1-10 percent. It should be noted that even though smaller K values are used by this dissertation compared to Wagner and Ragatz (1994), they used a more congested job shop (a utilization of 85 percent compared to 80 percent). Kher et al. (2000) used a flow shop with utilizations of 70 and 90 percent; particularly for the shop with 90 percent utilization, higher K values would be more appropriate.

3.3 Dependent variables

Simulation allows a variety of performance metrics to be collected relatively easily. Thus, the measures seen in Figure 4 are collected for each treatment.

Performance Classification	Performance Measure	Code
Customer Service	Proportion of jobs tardy	PT
	Conditional mean tardiness	CMT
	Maximum tardiness	MT
	Mean lateness	ML
	Mean flow time of job	MFT
Inventory	Mean number of transfer lots in system	MTL
Logistics	Material movements	MM
Capacity	Actual utilization	AU

Figure 4. Performance measures (dependent variables) for experimental design

Most of the variables should be self-explanatory because of their common use in the scheduling, lot streaming, and operations literatures. Tardiness refers to jobs that arrive after their due date; a job that is early or on time is said to not be tardy and thus has a tardiness value of 0. On the other hand, a job that is early is said to be late and has a negative lateness value based on the difference between the completion dates and the due date. CMT is computed by dividing MT by PT. The flow time calculations are based on the time it takes from a job to be released to the system until all transfer lots for that job have been completed. Kher et al. (2000) is the only other research that has examined the impact of increased lot streaming on the number of material movements, but they examined a flow shop (and not a job shop as in this research), and they modeled pull material movements slightly differently (see section 3.1 for more information). No RFID research has modeled the shop floor impact of RFID’s enabling characteristics on mean flow time (MFT), proportion tardy (PT), and material movements (MM). Because of the large number of factors and dependent variables, the dissertation will primarily focus on the PT, MFT, and MM metrics, and the relationship between them.

3.4 Basic hypotheses

Previous lot streaming research (Jacobs and Bragg, 1988; Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000; Litchfield and Narasimhan, 2000) has been exploratory and has not formally stated hypotheses. Instead, the lot streaming research using simulation has typically been meant to test the effect of the factors and their levels. Occasionally, expected results have been expressed, such as the following from Smunt et al. (1996): "We expected that the impact of increasing the number of transfer batches will be more dramatic for higher levels of the setup ratio, for higher processing utilization levels, and higher levels of variability (CV). We also expected that as the number of transfer batches gets very large, so the expected transfer batch size approaches 1, deleterious effects of lot splitting will appear in the job shop." This dissertation presents the less formal expected results sometimes seen in previously published lot streaming research, as well as more formal and statistically precise *alternative* (not null) hypotheses.

H1. The forms of bar coding with stochastic read times should show worse mean flow time (MFT) and proportion tardy (PT) performance than their deterministic bar coding counterparts. Stated more formally, TM4 should have higher MFT and PT than TM2, and TM5 should have higher MFT and PT than TM3, statistically significant at no more than $p<.10$ when performing pairwise comparisons. This would be congruent with the basic queuing and "factory physics" principles discussed in Hopp and Spearman (2001), that increasing variability degrades the performance of a manufacturing system.

H2. With increased transfer lots (NTL), mean flow time (MFT) and proportion of jobs tardy (PT) will improve when using RFID (with TM1). Stated more formally, with the tracking mechanism held constant at level TM1, increasing NTL should result in increasingly smaller MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. When *not* using RFID (when not using TM1), increased NTL will result in better MFT and PT performance at first, and then lead to worse performance. Stated more formally, when using TM2 - TM5, increasing NTL should result in increasingly smaller MFT and PT up to some switchover point, before further increasing NTL results in increasingly larger MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. This issue has not been previously researched, but is based on the idea that the time spent performing the bar code tracking activity for an increasing number of transfer lots will eventually offset any performance gains from using increased lot streaming.

H3. The improvement in mean flow time (MFT) and proportion of jobs tardy (PT) performance with increased lot streaming (higher NTL) should be lower when the setup / processing time ratio increases (when SPR increases). Stated more formally, an NTL*SPR interaction effect (statistically significant at no more than p<.10) is expected to be identified for MFT and PT. This is compatible with the data from Smunt et al. (1996).

H4. With the tracking mechanism held constant at RFID (TM1), increasing the amount of lot streaming (NTL) should result in increasingly numerous material movements (MM), statistically significant at no more than $p < .10$ when performing pairwise comparisons between adjacent NTL levels. Such findings for the job shop modeled in this dissertation would be compatible with the flow shop study by Kher et al. (2000).

H5. Mean flow time (MFT) and proportion of jobs tardy (PT) should increase (be worse) with more read batching (with greater RB). Stated more formally, increasing levels of RB should result in higher MFT and PT, statistically significant at no more than $p < .10$. This is because with increased read batching, it is more likely that a downstream work center will choose a different job type to process, and thus waste capacity on performing a new setup for that other job type.

H6. Mean flow time (MFT) should be best with the shortest processing (SPT) dispatching rule (SDR2). When due dates are tight (K1), then proportion of jobs tardy (PT) should be best for the SPT dispatching rule (SDR2). When due dates are loose (K2), then PT should be best for the earliest operation due date (ODD) dispatching rule (SDR3). Stated more formally, the SPT rule (SDR2) is expected to be statistically better (at no more than p<.10) than FCFS (SDR1) and ODD (SDR3) for MFT. An SDR*K interaction effect is expected to be identified for the proportion of jobs tardy (PT), with the SPT rule (SDR2) being statistically better (at no more than $p<.10$) with tight due dates (K1), and the ODD rule (SDR3) being statistically better (at no more than $p<.10$) for loose due dates (K2). This would be compatible with the findings of Baker (1984) and Jayamohan and Chandrasekharan (2000).

H7. Proportion of jobs tardy (PT) performance should be better when there is more slack allowance for due dates (K2). Stated more formally, the K2 due date multiplier factor level should result in smaller PT (statistically significant at no more than $p < .10$) compared to when the K1 factor level is used. This is based on the basic characteristics of the TWK due date rule that calculates later due dates when using a higher multiplier.

3.5 Expected contributions

As noted in the earlier sub-sections on the fixed and multi-level factors, many of the factor combinations (particularly those that relate to RFID and pull material movement) have not been studied together in previous research. Identifying 1) the shape of the various performance curves (e.g., possible diminishing returns from increased lot streaming), 2) interactions between the different factors, and 3) the nature of performance trade-offs under various scenarios are also important contributions. Below are some of the expected contributions from this dissertation.

1. **Identification of conditions conducive to achieving ROI from RFID.** As noted earlier, the business case to implement RFID with justifiable ROI has been

difficult or impossible for many companies to make, particularly manufacturers (Byrnes, 2003; Bacheldor, 2005; Hoffman, 2005; Murphy, 2005b; Smyrlis, 2005). The literature review and experimental design have made a strong case of why RFID might be able to help improve performance in job shops. The simulation model should provide quantitative insight into what conditions, if any, are likely to result in benefits that offset the costs of using RFID (including operational trade-offs such as increased material movements).

2. **Demonstration of the value of "visibility" on the shop floor.** Visibility is often cited as an expected benefit of RFID (Srivastava, 2004; Bacheldor, 2005), but its real value is unclear (Sliwa, 2004; McClenahen, 2005; Quinn, 2005). This research should show how continuous, automated visibility from RFID can support traceability that is itself valuable (e.g., for recalls and process improvement that are not measured by this model) while also facilitating the improvement of flow time and tardiness performance measures. The latter benefits are expected to be indirectly obtained as a result of RFID enabling improvements in the way processes are executed (e.g., increased use of smaller lot sizes via lot streaming and improved data collection process conformance through reduced read batching).

3. **Quantitative perspective of RFID's benefits that is based on generalizable and previously accepted models.** Much of the RFID literature thus far has been qualitative or company-specific (Gilmore and Fralick, 2005; Murphy-Hoye et al., 2005).

4. **Analysis of RFID in the context of job shops.** As of this writing, nearly all of the RFID research has focused on high-volume repetitive processes with linear flows. For example, Gaukler and Hausman (under review) looked at the use of RFID in an assembly line, and Hou and Huang (2006) examined tagging each item in printing industry supply chains.
5. **Quantitative comparison of RFID and bar coding.** RFID may provide only slightly better performance than its low cost alternative (bar coding), which has important implications for manufacturers (McFarlane and Sheffi, 2003; Woods, 2003). Unfortunately, not much analysis has been done for this issue.
6. **Quantitative examination of the effect of lot streaming on material movements in job shops.** Earlier research has been qualitative or focused on flow shops (Kher et al., 2000).
7. **Analysis of the effect of time needed to track transfer lots when using increasingly more frequent lot streaming.** Previous lot streaming research has not quantitatively considered the time needed to track the transfer lots (e.g., with bar coding).
8. **Consideration of common dispatching rules generally shown to have better customer service and inventory performance than the rule most commonly used in past lot streaming research.** Previous lot streaming research (Wagner and Ragatz, 1994; Smunt et al., 1996; Kher et al., 2000) reached conclusions about the efficacy of using increased transfer lots while primarily using a

dispatching rule (FCFS) that has been shown to have relatively poor performance (Wagner and Ragatz, 1994).

3.6 Methodological issues

Simulation can generate data for thousands of different factor level combinations, but appropriate statistical techniques need to be chosen to avoid erroneous conclusions by making comparisons across all of the combinations. ANOVA and its associated post-hoc techniques are the methodologies most commonly used to avoid increasing type-I error rates (rejecting the null hypothesis when it should be retained) beyond acceptable family-wise levels.

Statistical power tests were performed to determine that 10 replications for each of the 2700 treatment combinations would provide sufficient statistical power to detect up to three-way interactions. Common random numbers were used for each of the 2700 treatment combinations. As suggested by Law and Kelton (2000), Banks, Carson II, Nelson, and Nicol (2001), and Kelton et al. (2004), unique random number streams are used for each of the different event types that can occur, helping synchronize each of the replications across the treatments. The use of common random numbers across treatments, with distinct streams within a treatment, facilitates a reduction in variance, thus increasing statistical power (Law and Kelton, 2000; Banks et al., 2001; Kelton et al., 2004). The Arena simulation software automatically splits the different random number streams into sub-streams that are used to further synchronize the use of replications across treatments (Kelton et al., 2004), an approach advocated by Law and Kelton (2000) and Banks et al (2001). It should also be noted that the cycle length of the Arena random number generator has good statistical properties (e.g., uncorrelated number generation) and has a cycle length of 3.1 x 10^{57} before the generated random numbers begin to repeat (Kelton et al., 2004). To avoid producing results for the final simulation model that could have been biased by results from pilots, different random number seeds were used for the different stages of model development.

When a job arrives in the system, its routing and processing time are immediately assigned to it, as was suggested by Law and Kelton (2000) and Banks et al. (2001) to facilitate synchronization of the conditions for the different treatments. The following event types had their own random number streams:

1. Interarrival stream
2. Expected operation time stream
3. Expected read time stream
4. Number of operations per routing stream
5. Work center assignment stream
6. Read batching probability stream

Graphical plots were produced to identify that transient warm-up conditions had been surpassed by 1600 hours and that steady state had therefore been produced (Suresh and Meredith, 1994; Smunt et al., 1996; Kelton et al., 2004). It should be noted that this was sufficient to allow approximately 1000 or more jobs to move through the system before statistics collection began. After the warm-up period, statistics were calculated for an additional 4000 hours. It is difficult to make comparisons of warm-up periods from previous research due to different system operating conditions (e.g., utilizations and number of work centers) and job characteristics (e.g., processing times), but some validation is possible based on more standard metrics such as the number of jobs. Litchfield and Narasimhan (2000) chose to “conservatively” discard the first 100 observations in their research of a job shop using lot streaming research that was modeled after Jacobs and Bragg (1988). Rohleder and Scudder (1993) discarded the first two hundred jobs to avoid initialization bias in their analysis of a job shop with six work centers and utilizations between 70 and 90 percent. Lejmi and Sabuncuoglu (2002) discarded the first three hundred jobs for their job shop with ten work centers and utilizations of 60 and 85 percent.

When simulation techniques such as common random numbers are used, they are by their nature designed to induce correlation across the treatment conditions for each of the replications so as to achieve a variance reduction in the point estimation of the mean difference between the treatment conditions, which in turn increases statistical power (Law and Kelton, 2000; Banks et al., 2001; Kelton et al., 2004). Because the samples for the treatment conditions are not statistically independent, techniques such as *basic* ANOVA or *independent sample* t-tests are not appropriate when common random numbers are used (Law and Kelton, 2000; Banks et al., 2001; Kelton et al., 2004).

Apart from the specific context of using common random numbers with simulation, Keppel (1991), Hays (1994), Kirk (1995) and Cohen, Cohen, West, and Aiken (2003) also discuss the necessity of using of blocking and repeated measures techniques that control for correlated samples. As Keppel (1991) indicated, with repeated measures (also known as within-subjects) designs, the treatment effects are represented by differences within a single group of subjects. Because some of the sources of variation have been isolated in the analysis to reflect differences within each subject, the error terms are different from, and ideally smaller than, completely randomized (also known as between-subjects) designs (Keppel, 1991). Hays (1994) describes repeated measures experimental designs as a logical extension of the idea of randomized block designs.

For this dissertation, each of the ten replications can be considered a subject to which the 2700 treatment conditions have been applied (a “pure” within-subjects design in the terminology of Keppel, 1991). The use of common random number streams makes this repeated measure design possible. Because the specific values for each of the replications have been chosen at random, the replication numbers are considered random effects (Hays, 1994). Together with the multi-level factors (described earlier) and their fixed effects, the overall experiment design is said to be mixed or Model III (Hays, 1994).

The statistical computer software package SPSS (version 14) offers a form of repeated measures ANOVA based on the general linear model (Field, 2005). One of the key assumptions of using repeated measures ANOVA is sphericity, but SPSS provides several F-ratio corrections for when the assumption is not met (Field, 2005). ANOVA is relatively insensitive to deviations from normally distributed residuals and homoscedastic populations, particularly with large sample sizes and equally sized experimental design cells (Hair, Anderson, Tatham, and Black, 1998; Mathews, 2005), which is the case with the dissertation model. With 10 replications for each of the 2700 treatment conditions, there are 27,000 observations, a very large sample size. As noted earlier, Arena’s random number generator has been developed to produce independent observations within a stream, and the repeated measures experimental design appropriately handles the correlations across treatment conditions for the same replication number that result because of the use of the common random numbers.

CHAPTER 4

SIMULATION MODEL VERIFICATION AND VALIDATION

Extensive work was done to verify and validate the simulation model. Based on the recommendations of Law and Kelton (2000), the following techniques were performed:

- The author explicitly reviewed the logic and program coding prior to running the simulation (section 4.1).
- The simulation was run interactively, and the results were compared against what was expected (section 4.2).
- Three types of log files of the simulation logic were compared against what was expected (section 4.3).
- The various factor settings for the simulation were reviewed for face validity by verifying that the output was reasonably within expectations (section 4.4).
- Simulation model results were compared against findings published in earlier research (Baker and Kanet, 1983; Baker, 1984) and were in agreement (section 4.5).
- The performance of a real-world manufacturer that uses RFID was replicated with the same simulation toolset (section 4.5).

4.1. Review of code logic

Arena is a very commonly used simulation package (Terzi and Cavalieri, 2004). According to the publisher of Arena, 45 percent of the papers of the 2005 Proceedings of the Winter Simulation Conference mentioned Arena, far more often than the next closest simulation competitor (Rockwell Automation, 2006). The built-in components of Arena act as standard building blocks that can be confidently used for elaborate simulations (Kelton et al., 2004).

As indicated in the Vita section of this dissertation, the author has extensive software development experience that included specific responsibilities related to software quality assurance. He was designated the lead engineer in the United States for MRP, MPS, and manufacturing supply chain functionality for Baan, one of the leading enterprise resource planning (ERP) vendors of the 1990s. He worked extensively debugging, enhancing, documenting, and validating that software, which was far more complex than the simulation model used for this dissertation. The dissertation simulation code was reviewed from start to end, and the few issues that were identified were corrected.

4.2. Interactive verification of simulation runs

Special functionality was developed to facilitate interactive verification and analysis beyond what is possible with the Arena debugger. After the simulation begins, a window appears that allows the model to be run based on ranges of the experimental design factor levels or by specifying the full range of controllable parameters (Figure 5). If the latter option is chosen, a tabbed window appears that allows each parameter to be precisely selected (Figure 6, Figure 7, Figure 8, Figure 9). Informational fields (e.g., aggregations of processing times) are updated based on changes, and a default configuration can be quickly saved and restored. Selecting OK starts the simulation.

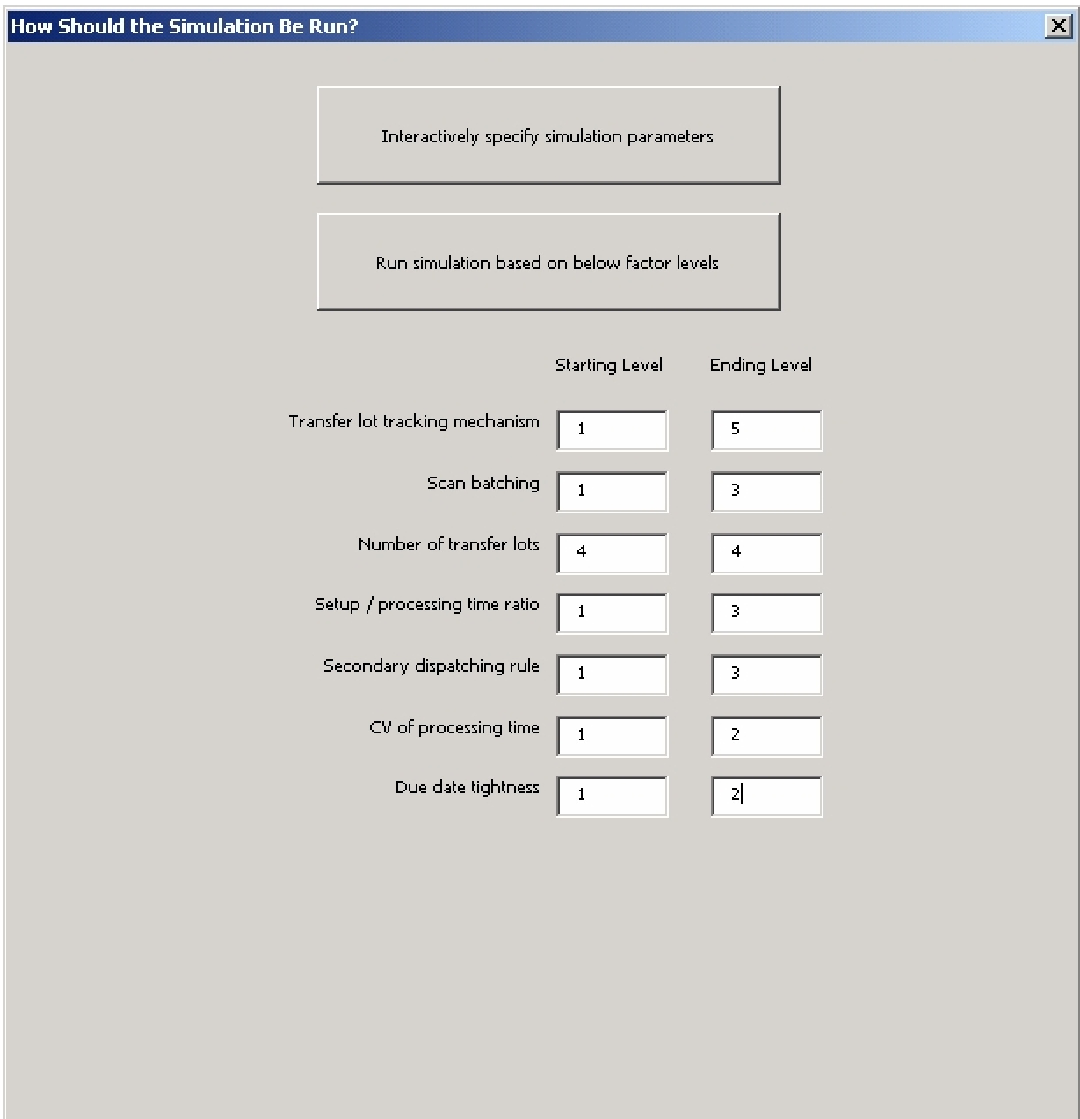


Figure 5. How should the Arena-based simulation be run?

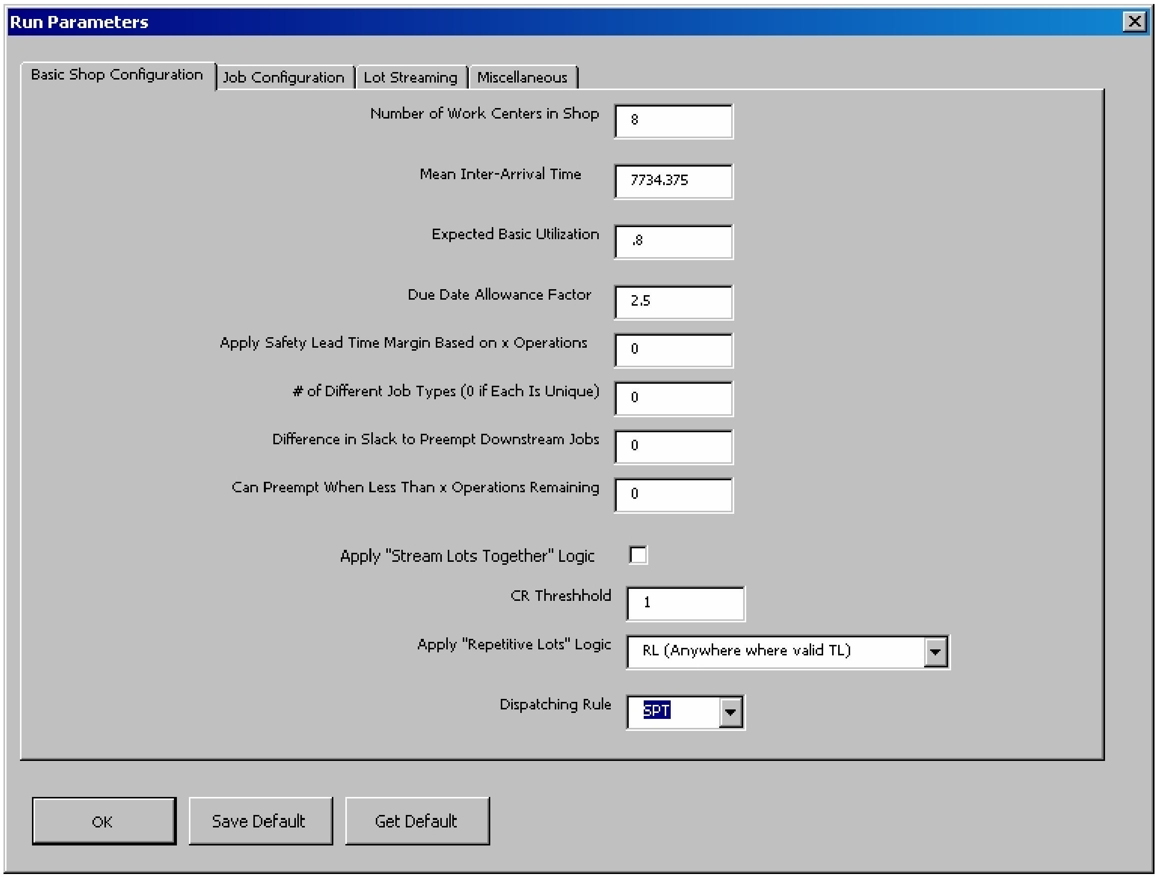


Figure 6. Tabbed window used to specify parameters for an interactive Arena-based simulation run (Basic Shop Configuration tab)

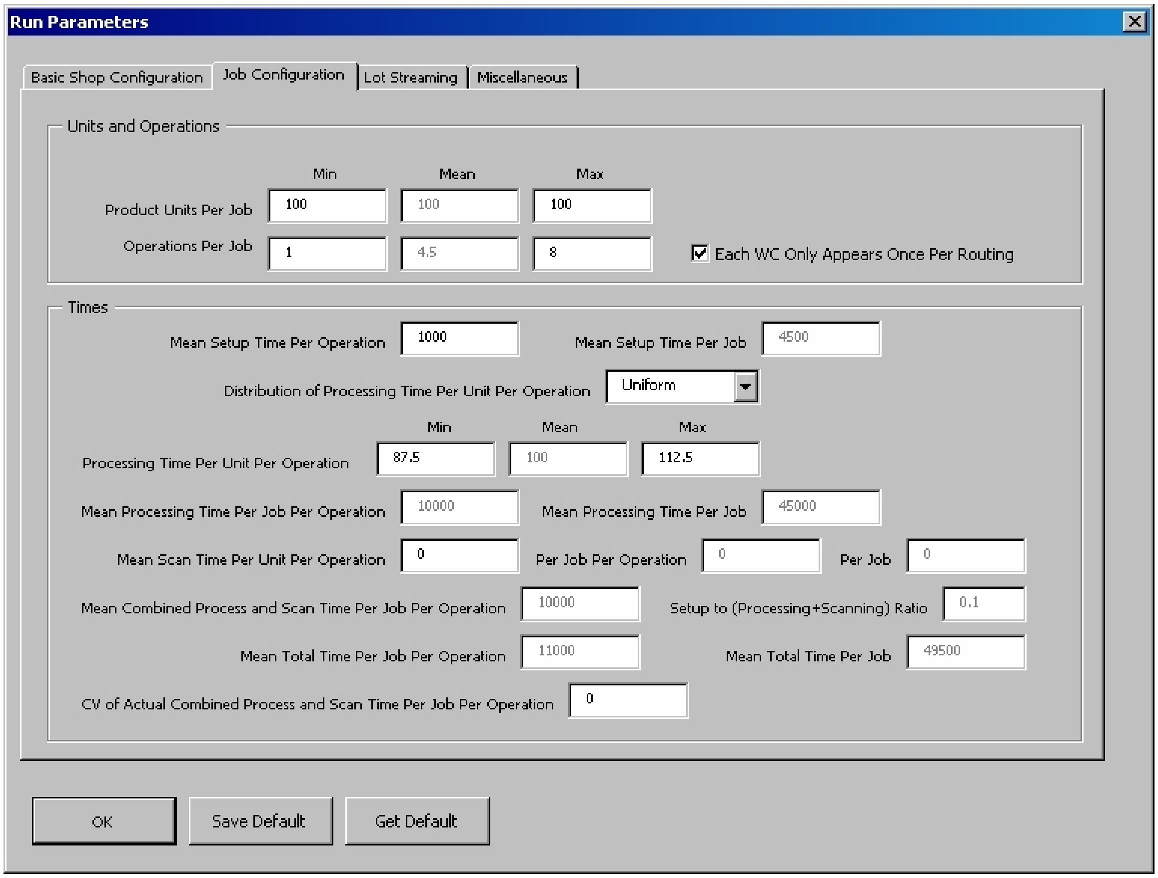


Figure 7. Tabbed window used to specify parameters for an interactive Arena-based simulation run (Job Configuration tab)

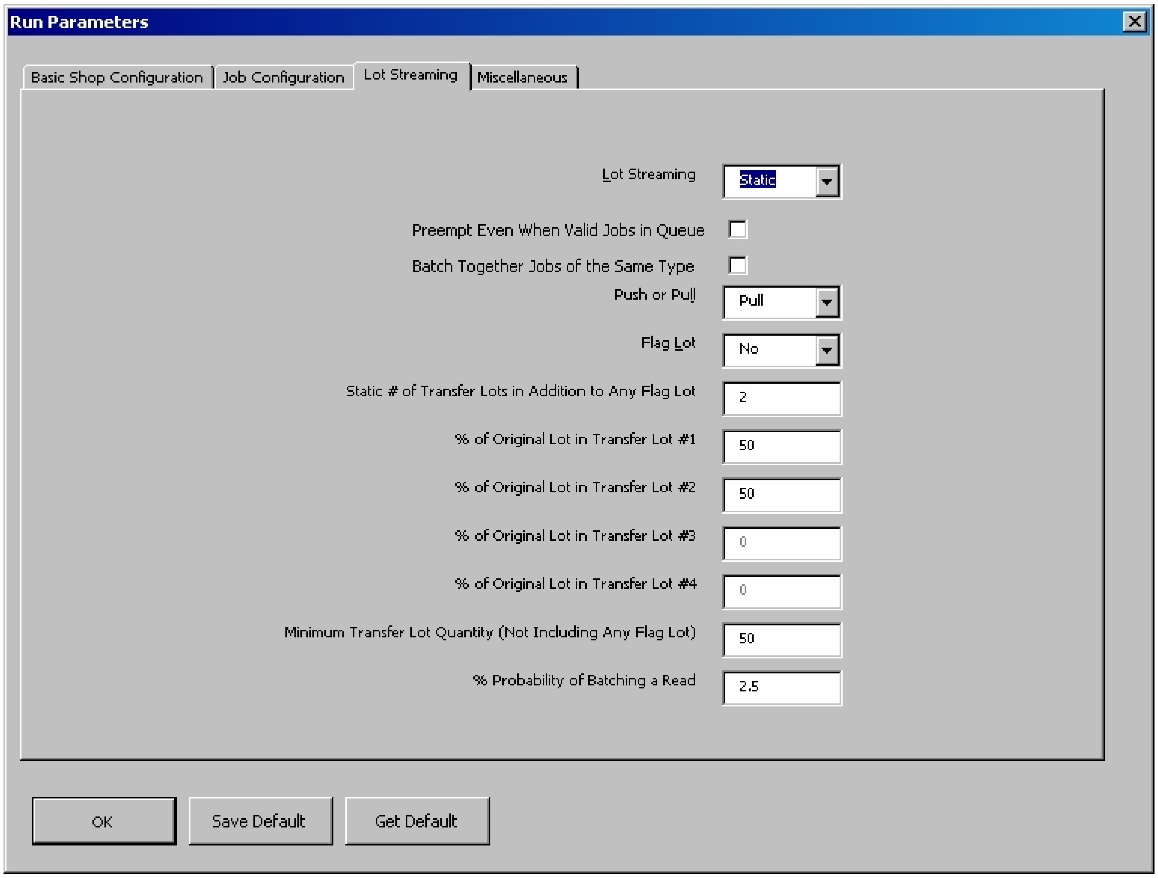


Figure 8. Tabbed window used to specify parameters for an interactive Arena-based simulation run (Lot Streaming tab)

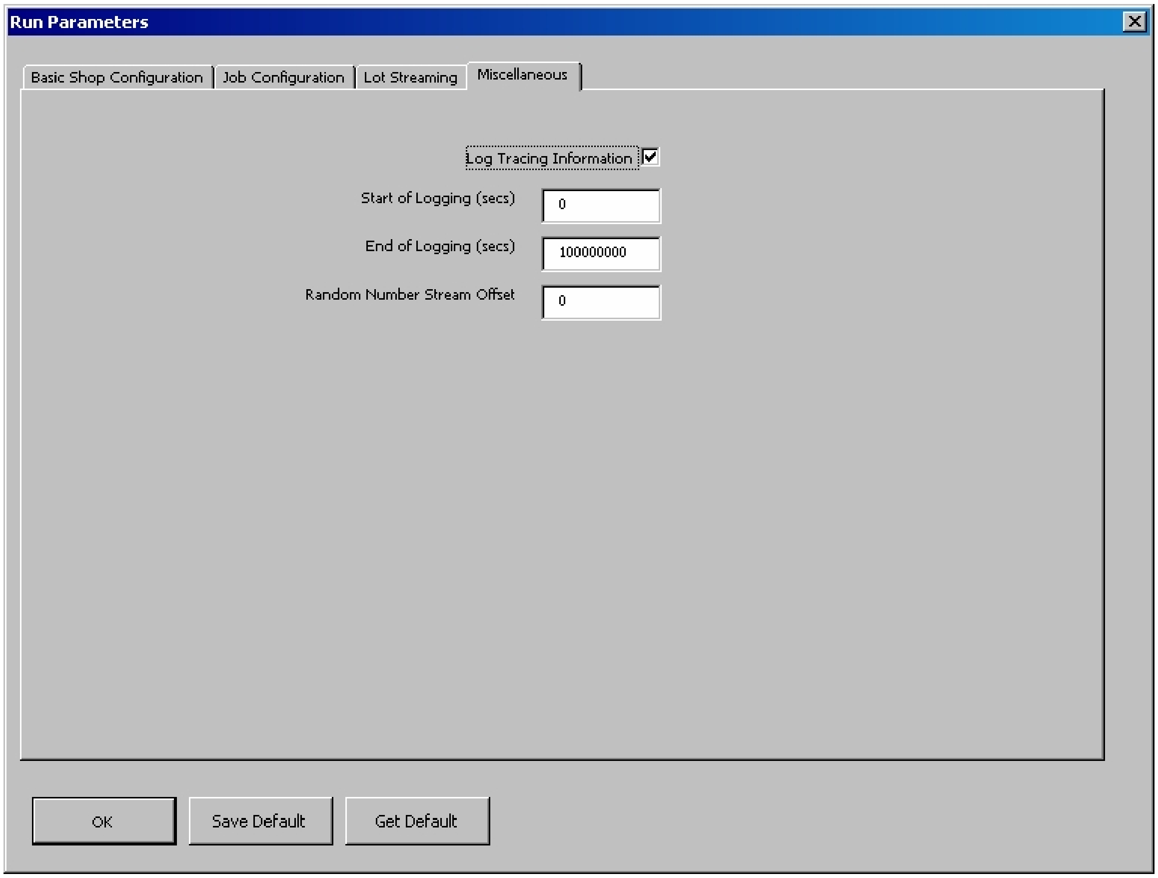


Figure 9. Tabbed window used to specify parameters for an interactive Arena-based simulation run (Miscellaneous tab)

When a major simulation event occurs, a tracking sub-window displays the current time, job number, transfer lot number, work center location, operation job step, and transfer lot unit quantity (Figure 10). The comments section in the tracking sub-window displays additional information about the nature of each event. The transfer lots at each work center are shown next to the tracking sub-window, and the transfer lot associated with the current event is shown in red. Icons for each job are shown at the bottom of the screen. The icons for transfer lots, jobs, and resources can be selected for context-specific information (Figure 11). Figure 12 provides a more detailed example of the tracking window, this time displaying the different transfer lots that were being evaluated for processing next at a work center. The information seen in the tracking window allowed the author to interactively verify that the output was correct for the various scenarios.

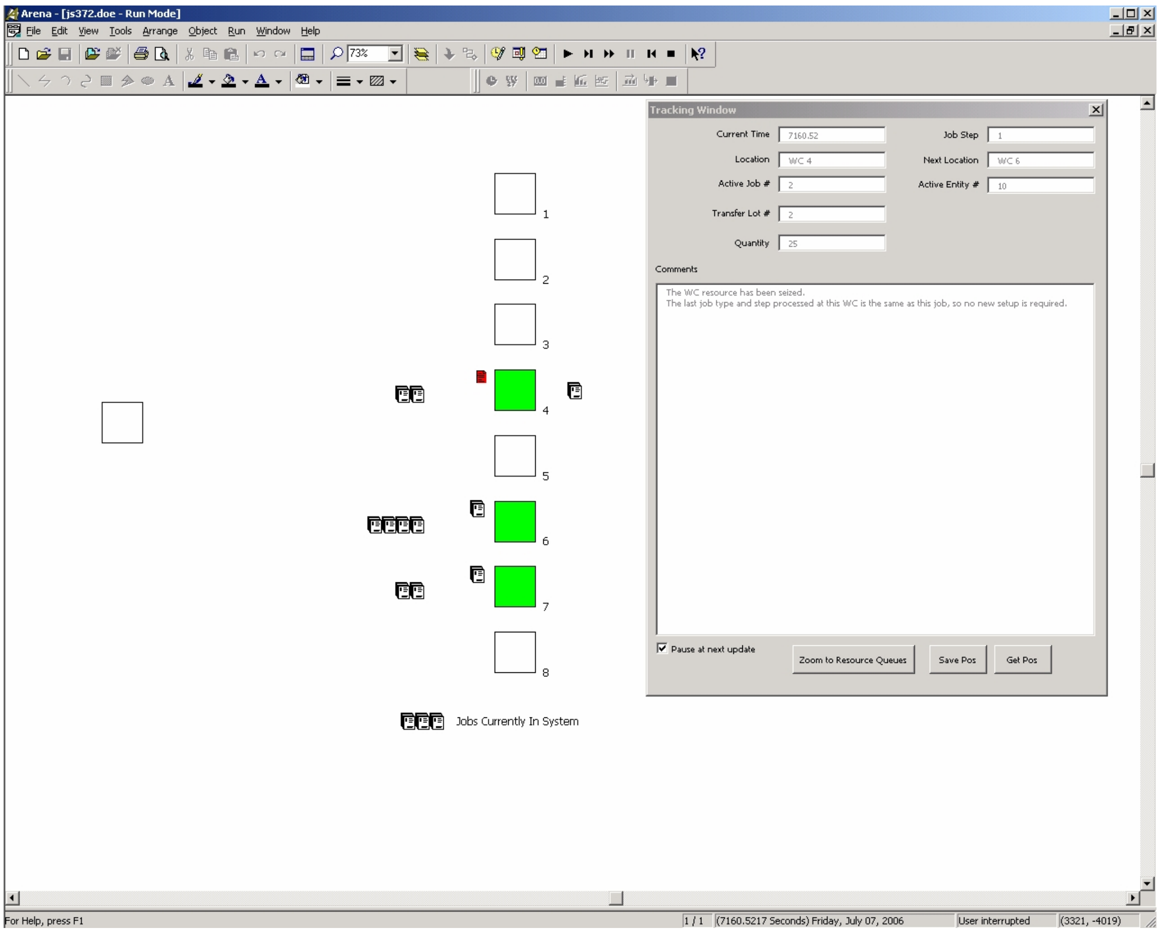


Figure 10. Example of an interactive Arena-based simulation run

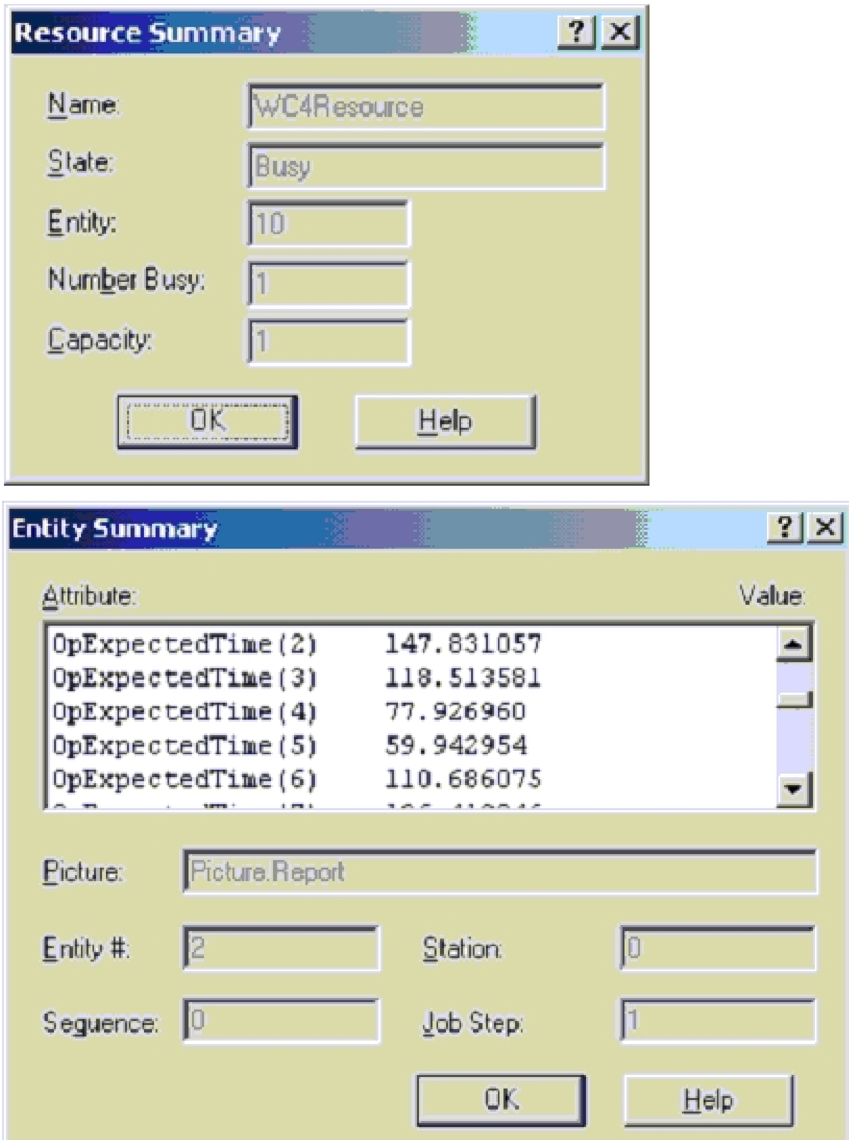


Figure 11. Example windows showing information about resources, jobs, and transfer lots

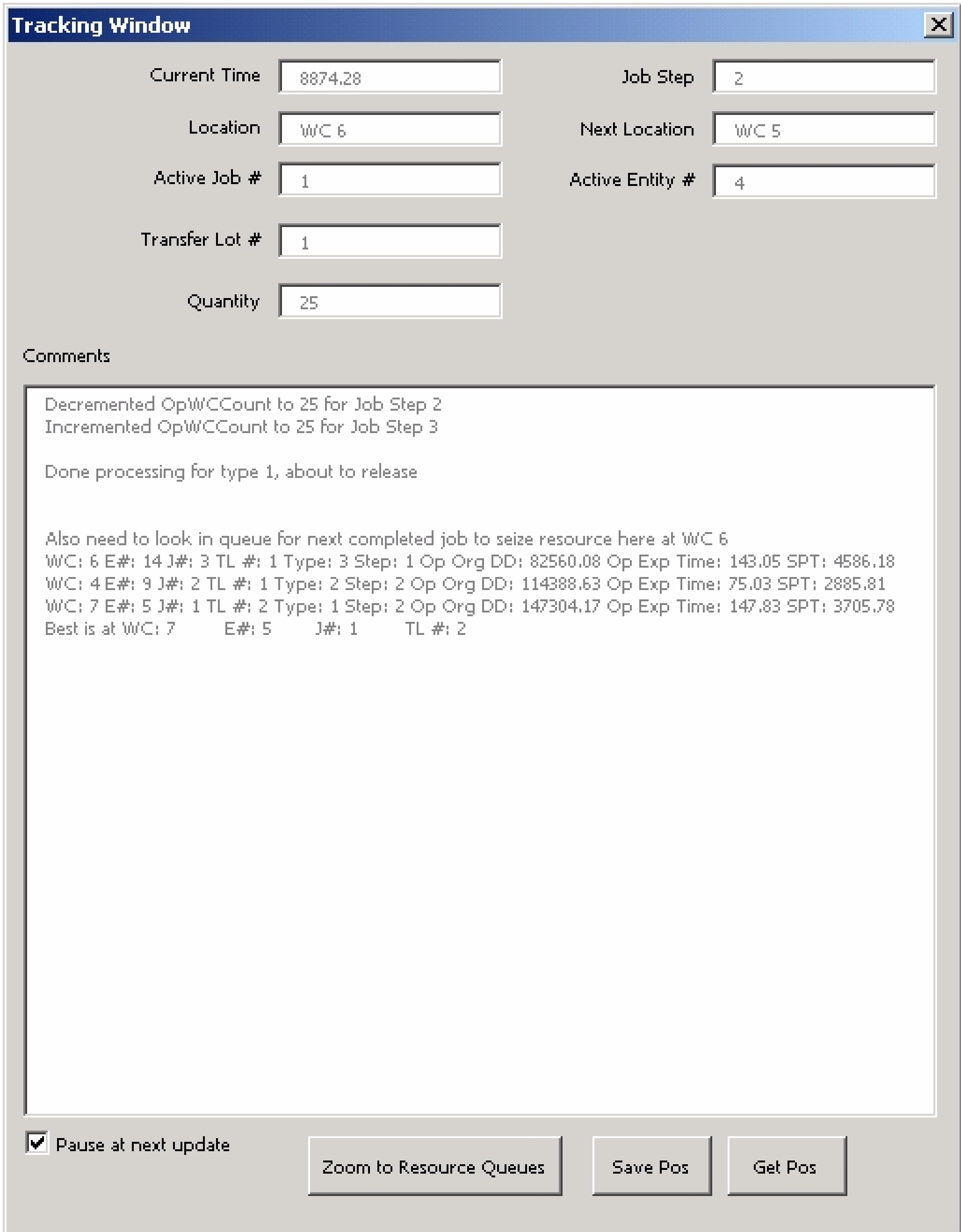


Figure 12. Interactive simulation run tracking window

4.3. Analysis of log file entries

The simulation allows log files to be created that record key events in the system, as well as the logic used whenever a decision is made. The log files are written to tab-delimited text files that are especially useful for importing into spreadsheets such as Microsoft Excel. Three kinds of logs are created:

1. A log showing when each job was created, along with information pertaining to the routing of each and operation due dates for each. This log's filename is always prefixed with "JobCreation".
2. A log showing the material movements of transfer lots between work centers. This log's filename is always prefixed with "QueueProcessing".
3. A log showing when transfer lots complete their processing. This log's filename is always prefixed with "TLCompletion".

The logs are created separately because of their distinct uses in debugging. Having separate log files makes it is easy to toggle back and forth between a window that shows the routing and operation due date information in the JobCreation log and a window that shows the more detailed material movement information in the QueueProcessing log. Similarly, when trying to identify why some jobs have tardy completions, it can be useful to toggle back and forth between a window that shows the TLCompletion log and a window that shows the QueueProcessing log.

Each log has a suffix that indicates the date and time the simulation run began, as well as the replication number. Because the log files can become quite large, each replication is assigned its own log file, which in turn allows Excel with its limitation of approximately 65000 rows to display more events for each replication. The date and time information in a log filename can be cross-referenced to another file that records the factor levels used for that simulation run. The configuration file is prefixed with "Configuration" and then the same date and time used for the log files. For example, the configuration used to produce log "JobCreation 0616170819 rep 1.txt" can be found in "Configuration 0616170819.txt" (the files were created on June 16 at 5:18:19 pm). Although the simulation logic uses non-rounded double decimal data types, all times written within the log files are rounded after two decimal places to improve readability.

A JobCreation log file consists of one row for each job. The columns indicate:

- The job number.
- The Arena entity number (primarily used for debugging).
- The job type (which will always be the same as the job number for this dissertation, because an "open" shop is simulated).
- The number of operations in the routing for this job.
- The due date for this job.
- The work center and expected processing times for each of the eight possible operation steps in the routing. If a job consists of less than eight operation steps, the corresponding entry is left blank.

The first six columns of each row in a QueueProcessing log always consist of:

- The simulation time,
- The current work center (where the event is taking place).
- The next work center (based on the routing for that job).
- The Arena entity number.
- The job number.
- The transfer lot number.

Depending on the nature of the event, one or more columns may follow in the same row. For example, there might be columns with arrival, processing time, and/or due date information for each of the transfer lots that were evaluated to determine which should be processed next at a work center.

A TLCompletion log consists of columns for:

- The job number of the transfer lot that was completed.
- The transfer lot number that was completed.
- The Arena entity number.
- The time the transfer lot was completed.
- The due date for the entire job.
- The operation step number of the "trailing" transfer lot for this job.

- A code that indicates whether this is the "trailing" (last) transfer lot for this job (-1 indicates that no other transfer lot for this job is further behind in the routing operation steps, 0 indicates that more transfer lots need to be processed before this job is completed).
- Another code with the same meaning as the immediately previous code, but is computed differently (different values would indicate problems in the upstream logic associated with each code).
- The number of transfer lots remaining.
- The number of transfer lots that were originally created for the job.

The following discussion will illustrate examples of how the log files were used for verification. The examples were created by running the simulation with two transfer lots of 50 units. Because the files contain so much information to facilitate debugging and verification, in some cases the logs were reformatted for the figures. The configuration file in Figure 13 shows the parameters that were used. Among the key parameters for this example, we see that the total work content (TWK) due date allowance factor was set to 2.5, the earliest due date by operation (ODD) rule is used (scheduling rule 3), there will always be 100 units per job, the mean setup time was 1000 seconds, and the mean scan time was a deterministic 10 seconds.

"nNumWCs",8
"dbMeanInterArrivalTime",7638.80938200237
"dbExpectedBasicUtilization",.811481173310168
"dbKAllowanceFactor",2.5
"nSafetyLeadTimeMarginOperations",0
"nNumDifferentJobTypes",0
"dbRequiredDifferenceToPreempt",0
"nPreemptWhenLessThanXOperationsRemaining",0
"nStreamLotsTogether",#FALSE#
"dbSLTThreshhold",1
"nRepetitiveLotsLogic",2
"nSchedulingRule",3
"nMinUnitsPerJob",100
"nMaxUnitsPerJob",100
"nMinOpsPerRouting",1
"nMaxOpsPerRouting",8
"nEachWCOnlyAppearsOncePerRouting",#TRUE#
"dbMeanSetupTime",1000
"nOpProcessingTimeDistribution",1
"dbMinExpectedOpTime",87.5
"dbMeanExpectedOpTime",100
"dbMaxExpectedOpTime",112.5
"dbMeanScanTime",10
"dbProcessScanTimeCV",0
"nLotStreaming",1
"nPreemptEvenWhenValidJobs",#FALSE#
"nBatchTogetherJobsOfSameType",#FALSE#
"nPushOrPull",1
"nFlagLot",0
"nNumberTransferLots",2
"dbPercentInLot1",50
"dbPercentInLot2",50
"dbPercentInLot3",0
"dbPercentInLot4",0
"nMinTransferLotQty",50
"dbReadBatchingProbability",2.5
"nLogTraceInformation",#TRUE#
"dbStartOfLogging",0
"dbEndOfLogging",100000000
"nRandomNumberStreamOffset",0
"WarmUpPeriod","1600"
"ReplicationLength","4800"
"NumberOfReplications","1"

Figure 13. Configuration file example

Figure 14 was created from the JobCreation log file. A job was created at approximately time 9.55 seconds with 8 operations and a job due date of 222663.24 seconds. The first operation for that job took place at work center 7, and took approximately 106.49 seconds per unit to process. Based on the TWK due date allowance factor, the due date for operation 1 was 29181.94. If you were to compute the due date by hand, you would likely calculate a value close to 29182.05. The reason for the discrepancy is that the actual processing time per unit was 106.489546560639 (not the rounded 106.49 shown in the log file), and the actual creation time of the job was at 9.55072007493804. These precise times can be seen when using the Arena debugger. The due dates for the rest of the operations were similarly computed, based on the non-rounded due date of each preceding operation.

J#	E#	Creation Time	Type	# Ops	Due Date	WC for Op 1	Op 1 Expected Time	Op 1 Orig Due Date	WC for Op 2	Op 2 Expected Time	Op 2 Orig Due Date	WC for Op 3	Op 3 Expected Time	Op 3 Orig Due Date	…
1	2	9.55	1	8	222663.24	7	106.49	29181.94	6	111.96	59721.38	5	104.63	88428.48	…
2	3	2939.03	2	2	58165.65	4	106.75	32176.14	6	93.76	58165.65	10	0	0	…
3	6	5764.51	3	5	146297.5	6	110.76	36004.96	5	92.68	61724.23	4	99.16	89063.36	…
4	9	19115.77	4	6	182292.53	1	94.13	45197.96	7	111.73	75681.05	5	91.08	101000.68	…
5	12	21029.7	5	2	78683.26	8	101.74	49015.95	7	108.47	78683.26	10	0	0	…
6	15	26852.56	6	2	81384.83	4	99.96	54393.73	8	97.76	81384.83	10	0	0	…
7	7	31859.16	7	5	170561.16	5	96.08	58429.32	8	108.76	88170.44	4	103.41	116573.06	…
8	8	35215.45	8	2	89117.05	4	93.14	61050.31	1	102.07	89117.05	10	0	0	…
9	21	36332.01	9	7	238443.46	2	109.9	66356.94	6	97.18	93200.98	7	111.91	123727.3	…

Figure 14. Information from a JobCreation log file

Figure 15 was created from the QueueProcessing log file, which records the movement of the transfer lots between work centers. At time 9.55, the two transfer lots (TL #: 1 and TL #: 2) of the first job (J#: 1) were created. Their current work center (as indicated by CWC) was 7, and their next destination was at work center 6 (as indicated by NWC). Because work center 7 was idle, the first transfer lot was able to seize it, but a setup had to be performed. At time 1009.55, the setup was done, and the processing for the 50 units of the transfer lot could be performed. At times 2939.03 and 5764.51, the transfer lots for job numbers 2 and 3 were created (cross-reference to Figure 14), and the first transfer lot of each seized work centers 4 and 6, respectively.

9.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 1; TJS: 1 TTL: 0 Count(1): 100
9.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 1009.55.
9.55	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100
1009.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5324.48 Actual completion of last unit: 6334.03
2939.03	CWC: 4	NWC: 6	E#: 7	J#: 2	TL #: 1	Arriving at an idle resource for job step 1; TJS: 1 TTL: 0 Count(1): 100
2939.03	CWC: 4	NWC: 6	E#: 7	J#: 2	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 3939.03.
2939.03	CWC: 4	NWC: 6	E#: 8	J#: 2	TL #: 2	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100
3939.03	CWC: 4	NWC: 6	E#: 7	J#: 2	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5337.42 Actual completion of last unit: 9276.45
5764.51	CWC: 6	NWC: 5	E#: 10	J#: 3	TL #: 1	Arriving at an idle resource for job step 1; TJS: 1 TTL: 0 Count(1): 100
5764.51	CWC: 6	NWC: 5	E#: 10	J#: 3	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 6764.51.
5764.51	CWC: 6	NWC: 5	E#: 11	J#: 3	TL #: 2	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100
6334.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
6344.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 6

In the log file, the below line is in a cell on the same line as the above row (to the right of the rightmost cell above):
E#: 5 J#: 1 TL #: 2 Type: 1 Step: 1 WC: 7 Op O DD: 29181.94 Op Exp Time for TL: 5334.48 BRM:29181.94 EDD: 29181.94
In the log file, the below line is in a cell on the same line as the above row (to the right of it)
Best is E#: 5 J#: 1 TL #: 2

6344.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 7 for job step 1; TJS: 1 TTL: 0 Count(1): 50
6344.03	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5324.48 Actual completion of last unit: 11668.51

Figure 15. Information from a QueueProcessing log file

At time 6334.03, the 50 units of transfer lot 1 of job 1 were completed, and they needed to be scanned in order to decide if the transfer lot should be moved to the next work center. Based on the parameter “% probability of batching a read”, there was a chance that work center 7 might not immediately scan the transfer lot, in which case the next work center (6) in the transfer lot’s routing would not have known that a transfer lot was ready to be moved there. In this example, we see in the log file that the scan did take place, and it took 10 seconds of the operator’s time at work center 7. At time 6344.03, transfer lot 1 of job 1 finished processing at work center 7, and work center 7 decided what to process next. Work center 7 examined each transfer lot that was either at work center 7 and waiting to be processed there, or was in a queue after one of the other work centers and had been scanned and was waiting to be moved to work center 7. In this case, only transfer lot 2 of job 1 was ready for processing at work center 7, and so it was noted as the best and selected for processing. Transfer lot 1 of job 1 eventually needed to move to work center 6, but it can be seen in Figure 8 that work center 6 was busy until 6764.51 with transfer lot 1 of job 3. Moving transfer lot 1 of job 1 to work center 6 at time 6344.03 would result in no benefit, so because of the pull philosophy, it was going to wait in a queue after work center 7 until it was either the highest priority transfer lot that was ready to be processed at work center 6, or it was pulled with the same material movement with another transfer lot from work center 7 to work center 6. The last row in Figure 15 shows that processing began for transfer lot 2 of job 1 at work center 7 at time

6344.03; because it was the same job type as was used immediately before at that work center, a new setup is not required.

The discussion in the previous paragraphs illustrates that the functionality for the following features worked correctly:

- Use of setup time.
- Use of scan time.
- Pull material movements.

The log files were designed to support easy sorting, filtering, and finding within Microsoft Excel. The following figures were created using Excel's filtering capability to highlight the movements from the QueueProcessing log for job 1. In instances when an entire row from the log file will not fit in a row for the figure (such as when the priorities of several transfer lots must be evaluated to determine what to process next at a work center), the rightmost cells from the log file are "wrapped" onto the rows immediately beneath the rest of their row. Some events of interest are discussed below:

- As seen in Figure 16, at time 11678.51, transfer lot 2 completed processing at work center 7. Work center 7 looked for something to process, but could not find anything (as was noted in the log file). This lack of utilization happened several other times at other work centers before job 1 completed processing at its last operation step.

9.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 1; TJS: 1 TTL: 0 Count(1): 100
9.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 1009.55.
9.55	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100
1009.55	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5324.48 Actual completion of last unit: 6334.03
6334.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
6344.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 6

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 1 WC: 7 Op O DD: 29181.94 Op Exp Time for TL: 5334.48 BRM:29181.94 EDD: 29181.94
Best is E#: 5 J#: 1 TL #: 2

6344.03	CWC: 7	NWC: 6	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 7 for job step 1; TJS: 1 TTL: 0 Count(1): 50
6344.03	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5324.48 Actual completion of last unit: 11668.51
11668.51	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
11678.51	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 6

There was nothing else already completed to select for processing now here at WC 7

11678.51	CWC: 7	NWC: 6	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 7 for job step 1; TJS: 2 TTL: -1 Count(1): 0
28256.49	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 2; TJS: 2 TTL: 0 Count(2): 100 Count(1): 0
28256.49	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 29256.49.
28256.49	CWC: 6	NWC: 5	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 2; will wait in queue; TJS: 2 TTL: -1 Count(2): 100 Count(1): 0
29256.49	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5597.89 Actual completion of last unit: 34854.38
34854.38	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
34864.38	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 5

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 2 WC: 6 Op O DD: 59721.38 Op Exp Time for TL: 5607.89 BRM:59721.38 EDD: 59721.38
Best is E#: 5 J#: 1 TL #: 2

34864.38	CWC: 6	NWC: 5	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 6 for job step 2; TJS: 2 TTL: 0 Count(2): 50 Count(3): 50
34864.38	CWC: 6	NWC: 5	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5597.89 Actual completion of last unit: 40462.27
40462.27	CWC: 6	NWC: 5	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
40472.27	CWC: 6	NWC: 5	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 5

There was nothing else already completed to select for processing now here at WC 6

40472.27	CWC: 6	NWC: 5	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 6 for job step 2; TJS: 3 TTL: -1 Count(2): 0 Count(3): 100
42487.23	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 3; TJS: 3 TTL: 0 Count(3): 100 Count(2): 0
42487.23	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 43487.23.
42487.23	CWC: 5	NWC: 8	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 3; will wait in queue; TJS: 3 TTL: -1 Count(3): 100 Count(2): 0
43487.23	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5231.42 Actual completion of last unit: 48718.65
48718.65	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10

Figure 16. Information from a QueueProcessing log file (filtered on "J#: 1"), part 1

- It can be seen in Figure 17 that at time 53970.07, when transfer lot 2 was completing processing at work center 5, work center 5 needed to compare transfer lot 1 of job 10 (that was waiting to be pulled from work center 6) to transfer lot 1 of job 4 (that was waiting to be pulled from work center 7). Because the operation due date for the former (job 10) was 103077.61, versus 101000.68 for the latter (job 4), the latter was chosen. This illustrates that the ODD functionality works correctly.

48728.65	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 8

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 3 WC: 5 Op O DD: 88428.48 Op Exp Time for TL: 5241.42 BRM:88428.48 EDD: 88428.48
Best is E#: 5 J#: 1 TL #: 2

48728.65	CWC: 5	NWC: 8	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 5 for job step 3; TJS: 3 TTL: 0 Count(3): 50 Count(4): 50
48728.65	CWC: 5	NWC: 8	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5231.42 Actual completion of last unit: 53960.07
53960.07	CWC: 5	NWC: 8	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
53970.07	**CWC: 5**	NWC: 8	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 8

E#: 18 **J#: 10 TL #: 1** Type: 10 Step: 2 WC: 6 Op O DD: 103077.61 Op Exp Time for TL: 6525.83 BRM:103077.61 EDD: 103077.61
E#: 13 **J#: 4 TL #: 1** Type: 4 Step: 3 WC: 7 Op O DD: 101000.68 Op Exp Time for TL: 5563.93 BRM:101000.68 EDD: 101000.68
Best is E#: 13 J#: 4 TL #: 1

53970.07	CWC: 5	NWC: 8	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 5 for job step 3; TJS: 4 TTL: -1 Count(3): 0 Count(4): 100
57593.23	CWC: 8	NWC: 1	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 4; TJS: 4 TTL: 0 Count(4): 100 Count(3): 0
57593.23	CWC: 8	NWC: 1	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 58593.23.
57593.23	CWC: 8	NWC: 1	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 4; will wait in queue; TJS: 4 TTL: -1 Count(4): 100 Count(3): 0
58593.23	CWC: 8	NWC: 1	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 4724.09 Actual completion of last unit: 63317.31
63317.31	CWC: 8	NWC: 1	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
63327.31	CWC: 8	NWC: 1	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 1

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 4 WC: 8 Op O DD: 114598.91 Op Exp Time for TL: 4734.09 BRM:114598.91 EDD: 114598.91
Best is E#: 5 J#: 1 TL #: 2

63327.31	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 5; TJS: 4 TTL: 0 Count(5): 50 Count(4): 50
63327.31	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 64327.31.
63327.31	CWC: 8	NWC: 1	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 4724.09 Actual completion of last unit: 68051.4
64327.31	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 4499.29 Actual completion of last unit: 68826.6
68051.4	CWC: 8	NWC: 1	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
68061.4	CWC: 8	NWC: 1	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 1

There was nothing else already completed to select for processing now here at WC 8

68061.4	CWC: 8	NWC: 1	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 8 for job step 4; TJS: 5 TTL: -1 Count(4): 0 Count(5): 100
68826.6	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
68836.6	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 4

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 5 WC: 8 Op O DD: 139645.35 Op Exp Time for TL: 4509.29 BRM:139645.35 EDD: 139645.35
Best is E#: 5 J#: 1 TL #: 2

68836.6	CWC: 1	NWC: 4	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 1 for job step 5; TJS: 5 TTL: 0 Count(5): 50 Count(6): 50
68836.6	CWC: 1	NWC: 4	E#: 5	J#: 1	TL #: 2	Arriving at an idle resource for job step 5; TJS: 5 TTL: -1 Count(5): 50 Count(4): 0
68836.6	CWC: 1	NWC: 4	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 4499.29 Actual completion of last unit: 73335.89
73335.89	CWC: 1	NWC: 4	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
73345.89	CWC: 1	NWC: 4	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 4

Figure 17. Information from a QueueProcessing log file (filtered on "J#: 1"), part 2

- Figure 18 shows that at time 136525.90, transfer lot 1 completed processing at work center 2, but waited in queue after work center 2 because work center 3 was busy. Transfer lot 2 began processing then and completed processing at work center 2 at time 141866.14, but it also waited in queue after work center 2 because work center 3 was still busy. It was not until 146776.34 that both transfer lots for job 1 were moved to work center 3, and even then, they had to wait until 157010.12 and 162629.88, respectively, to begin processing there (shown in Figure 19). This illustrates that the pull movements worked correctly (parts wait to be pulled, and when one part moves to the next work center because it has the highest priority, so do the other parts in the same source queue that have that same destination).

E#: 19 J#: 13 TL #: 1 Type: 13 Step: 2 WC: 2 Op O DD: 120963.49 Op Exp Time for TL: 6599.32 BRM:120963.49 EDD: 120963.49
Best is E#: 19 J#: 13 TL #: 1

73345.89	CWC: 1	NWC: 4	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 1 for job step 5; TJS: 6 TTL: -1 Count(5): 0 Count(6): 100
106223.04	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 6; TJS: 6 TTL: 0 Count(6): 100 Count(5): 0
106223.04	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 107223.04.
106223.04	CWC: 4	NWC: 2	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 6; will wait in queue; TJS: 6 TTL: -1 Count(6): 100 Count(5): 0
107223.04	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5133.58 Actual completion of last unit: 112356.62
112356.62	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
112366.62	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 2

E#: 19 J#: 13 TL #: 1 Type: 13 Step: 4 WC: 4 Op O DD: 178257.76 Op Exp Time for TL: 5952.45 BRM:178257.76 EDD: 178257.76
E#: 5 J#: 1 TL #: 2 Type: 1 Step: 6 WC: 4 Op O DD: 167863.23 Op Exp Time for TL: 5143.58 BRM:167863.23 EDD: 167863.23
Best is E#: 5 J#: 1 TL #: 2

112366.62	CWC: 4	NWC: 2	E#: 4	J#: 1	TL #: 1	Will wait in queue after resource 4 for job step 6; TJS: 6 TTL: 0 Count(6): 50 Count(7): 50
112366.62	CWC: 4	NWC: 2	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5133.58 Actual completion of last unit: 117500.19
117500.19	CWC: 4	NWC: 2	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
117510.19	CWC: 4	NWC: 2	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 2

E#: 19 J#: 13 TL #: 1 Type: 13 Step: 4 WC: 4 Op O DD: 178257.76 Op Exp Time for TL: 5952.45 BRM:178257.76 EDD: 178257.76
Best is E#: 19 J#: 13 TL #: 1

117510.19	CWC: 4	NWC: 2	E#: 5	J#: 1	TL #: 2	Will wait in queue after resource 4 for job step 6; TJS: 7 TTL: -1 Count(6): 0 Count(7): 100
130185.66	CWC: 2	NWC: 3	E#: 4	J#: 1	TL #: 1	Arriving at an idle resource for job step 7; TJS: 7 TTL: 0 Count(7): 100 Count(6): 0
130185.66	CWC: 2	NWC: 3	E#: 4	J#: 1	TL #: 1	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 131185.66.
130185.66	CWC: 2	NWC: 3	E#: 5	J#: 1	TL #: 2	Arriving at a busy resource for job step 7; will wait in queue; TJS: 7 TTL: -1 Count(7): 100 Count(6): 0
131185.66	CWC: 2	NWC: 3	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5330.24 Actual completion of last unit: 136515.9
136515.9	CWC: 2	NWC: 3	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
136525.9	CWC: 2	NWC: 3	E#: 4	**J#: 1**	**TL #: 1**	**Done processing for type 1**, about to release and move to WC 3

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 7 WC: 2 Op O DD: 197064.41 Op Exp Time for TL: 5340.24 BRM:197064.41 EDD: 197064.41
Best is E#: 5 J#: 1 TL #: 2

136525.9	CWC: 2	**NWC: 3**	E#: 4	J#: 1	TL #: 1	**Will wait in queue after resource 2** for job step 7; TJS: 7 TTL: 0 Count(7): 50 Count(8): 50
136525.9	CWC: 2	NWC: 3	E#: 5	J#: 1	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5330.24 Actual completion of last unit: 141856.14
141856.14	CWC: 2	NWC: 3	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
141866.14	CWC: 2	NWC: 3	E#: 5	J#: 1	TL #: 2	Done processing for type 1, about to release and move to WC 3

E#: 31 J#: 24 TL #: 1 Type: 24 Step: 1 WC: 2 Op O DD: 159922.21 Op Exp Time for TL: 5936.33 BRM:159922.21 EDD: 159922.21
Best is E#: 31 J#: 24 TL #: 1

141866.14	CWC: 2	NWC: 3	E#: 5	**J#: 1**	**TL #: 2**	**Will wait in queue after resource 2** for job step 7; TJS: 8 TTL: -1 Count(7): 0 Count(8): 100
146776.34	CWC: 3	NWC: 10	E#: 4	**J#: 1**	**TL #: 1**	**Arriving at a busy resource** for job step 8; will wait in queue; TJS: 8 TTL: 0 Count(8): 100 Count(7): 0

Figure 18. Information from a QueueProcessing log file (filtered on “J#: 1”), part 3

146776.34	CWC: 3	NWC: 10	E#: 5	**J#: 1**	**TL #: 2**	**Arriving at a busy resource** for job step 8; will wait in queue; TJS: 8 TTL: -1 Count(8): 100 Count(7): 0
157010.12	**CWC: 3**	NWC: 10	E#: 4	**J#: 1**	**TL #: 1**	**Resource seized**. Different type or step than previously at WC, new setup of 1000.Completion for setup at 158010.12.
158010.12	CWC: 3	NWC: 10	E#: 4	J#: 1	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 4609.77 Actual completion of last unit: 162619.88
162619.88	CWC: 3	NWC: 10	E#: 4	J#: 1	TL #: 1	We will scan 1 transfer lots, taking a time of 10
162629.88	CWC: 3	NWC: 10	E#: 4	J#: 1	TL #: 1	Done processing for type 1, about to release and move to WC 10

E#: 5 J#: 1 TL #: 2 Type: 1 Step: 8 WC: 3 Op O DD: 222663.24 Op Exp Time for TL: 4619.77 BRM:222663.24 EDD: 222663.24
Best is E#: 5 J#: 1 TL #: 2

162629.88	CWC: 10	NWC: X	E#: 4	**J#: 1**	**TL #: 1**	**Completing TL.There are more TLs remaining for this job.**
162629.88	**CWC: 3**	NWC: 10	E#: 5	J#: 1	**TL #: 2**	**Beginning 50 units in the TL.** Actual process time for TL: 4609.77 Actual completion of last unit: 167239.65
167239.65	CWC: 3	NWC: 10	E#: 5	J#: 1	TL #: 2	We will scan 1 transfer lots, taking a time of 10
167249.65	CWC: 3	NWC: 10	E#: 5	**J#: 1**	**TL #: 2**	**Done processing** for type 1, about to release and move to WC 10

E#: 23 J#: 16 TL #: 1 Type: 16 Step: 5 WC: 7 Op O DD: 224820.79 Op Exp Time for TL: 5834.94 BRM:224820.79 EDD: 224820.79
Best is E#: 23 J#: 16 TL #: 1

167249.65	CWC: 10	NWC: X	E#: 5	**J#: 1**	**TL #: 2**	**Completing TL. Last TL for job. Job was not tardy.**

Figure 19. Information from a QueueProcessing log file (filtered on “J#: 1”), part 4

- Figure 19 indicates that at time 167249.65, transfer lot 2 completed the last operation, and as noted, the job was not tardy (which could be verified by comparing back to the job's due date in the JobCreation file seen in Figure 14). This illustrates the correct recording of job completion information.

The QueueProcessing log file can be used for further debugging and verification. For example, the logic can be investigated to see why it took so long for transfer lots 1 and 2 to be moved to work center 3 and then begin processing. The file can be filtered on "CWC: 3" in the second column. The results are shown in Figure 20.

135256.18	**CWC: 3**	NWC: 1	E#: 14	**J#: 21**	**TL #: 1**	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 136256.18.
136256.18	CWC: 3	NWC: 1	E#: 14	J#: 21	TL #: 1	Beginning 50 units in the TL. Actual process time for TL: 5250.08 Actual completion of last unit: 141506.26
141506.26	CWC: 3	NWC: 1	E#: 14	J#: 21	TL #: 1	**We will scan this transfer lot later.**
141506.26	CWC: 3	NWC: 1	E#: 14	**J#: 21**	**TL #: 1**	Done processing for type 21, about to release and move to WC 1

E#: 9 **J#: 21 TL #: 2 Type: 21** Step: 1 WC: 3 Op O DD: 157494.05 Op Exp Time for TL: 5260.08 BRM:157494.05 EDD: 157494.05
Best is E#: 9 J#: 21 TL #: 2

141506.26	CWC: 3	NWC: 1	E#: 9	J#: 21	TL #: 2	Beginning 50 units in the TL. Actual process time for TL: 5250.08 Actual completion of last unit: 146756.34
146756.34	CWC: 3	NWC: 1	E#: 9	J#: 21	TL #: 2	**We will scan 2 transfer lots, taking a time of 20**
146776.34	CWC: 3	NWC: 1	E#: 9	J#: 21	TL #: 2	**Done processing** for type 21, about to release and move to WC 1

E#: 27 **J#: 19 TL #: 1** Type: 19 Step: 2 WC: 2 **Op O DD: 172060.19** Op Exp Time for TL: 5616.89 BRM:172060.19 **EDD: 172060.19**
E#: 4 **J#: 1 TL #: 1** Type: 1 Step: 8 WC: 2 **Op O DD: 222663.24** Op Exp Time for TL: 5619.77 BRM:172060.19 **EDD: 222663.24**
Best is E#: 27 J#: 19 TL #: 1

146776.34	CWC: 3	NWC: 1	E#: 9	J#: 21	TL #: 2	Will wait in queue after resource 3 for job step 1; TJS: 2 TTL: -1 Count(1): 0
146776.34	CWC: 3	NWC: 7	E#: 27	J#: 19	TL #: 1	Arriving at an idle resource for job step 2; TJS: 2 TTL: 0 Count(2): 100 Count(1): 0
146776.34	CWC: 3	NWC: 7	E#: 27	**J#: 19**	**TL #: 1**	**Resource seized.** Different type or step than previously at WC, new setup of 1000.Completion for setup at 147776.34.
146776.34	CWC: 3	NWC: 7	E#: 3	**J#: 19**	**TL #: 2**	**Arriving at a busy resource** for job step 2; will wait in queue; TJS: 2 TTL: -1 Count(2): 100 Count(1): 0
146776.34	CWC: 3	NWC: 10	E#: 4	**J#: 1**	**TL #: 1**	**Arriving at a busy resource** for job step 8; will wait in queue; TJS: 8 TTL: 0 Count(8): 100 Count(7): 0
146776.34	CWC: 3	NWC: 10	E#: 5	**J#: 1**	**TL #: 2**	**Arriving at a busy resource** for job step 8; will wait in queue; TJS: 8 TTL: -1 Count(8): 100 Count(7): 0
147776.34	CWC: 3	NWC: 7	E#: 27	J#: 19	TL #: 1	**Beginning 50 units in the TL.** Actual process time for TL: 4606.89 Actual completion of last unit: 152383.23
152383.23	CWC: 3	NWC: 7	E#: 27	J#: 19	TL #: 1	**We will scan 1 transfer lots**, taking a time of 10
152393.23	CWC: 3	NWC: 7	E#: 27	J#: 19	TL #: 1	**Done processing for type 19**, about to release and move to WC 7

E#: 3 **J#: 19 TL #: 2 Type: 19** Step: 2 WC: 3 Op O DD: 172060.19 Op Exp Time for TL: 4616.89 BRM:172060.19 EDD: 172060.19
Best is E#: 3 J#: 19 TL #: 2

152393.23	CWC: 3	NWC: 7	E#: 27	J#: 19	TL #: 1	Will wait in queue after resource 3 for job step 2; TJS: 2 TTL: 0 Count(2): 50 Count(3): 50
152393.23	CWC: 3	NWC: 7	E#: 3	**J#: 19**	**TL #: 2**	**Beginning 50 units in the TL.** Actual process time for TL: 4606.89 Actual completion of last unit: 157000.12
157000.12	CWC: 3	NWC: 7	E#: 3	J#: 19	TL #: 2	We will scan 1 transfer lots, taking a time of 10
157010.12	CWC: 3	NWC: 7	E#: 3	**J#: 19**	**TL #: 2**	**Done processing for type 19**, about to release and move to WC 7

E#: 4 **J#: 1 TL #: 1** Type: 1 Step: 8 WC: 3 **Op O DD: 222663.24** Op Exp Time for TL: 5619.77 BRM:222663.24 **EDD: 222663.24**
E#: 23 **J#: 16 TL #: 1** Type: 16 Step: 5 WC: 7 **Op O DD: 224820.79** Op Exp Time for TL: 5834.94 BRM:222663.24 **EDD: 224820.79**
Best is E#: 4 J#: 1 TL #: 1

Figure 20. Information from a QueueProcessing log file (filtered on "CWC: 3")

At time 135256.18, transfer lot 1 of job 21 began processing at work center 3. Its setup was completed at time 136256.18. Processing then began; because the processing for job 21 had a completion time of 141506.26, job 1 had to wait at least until then before it would have a chance to be considered for movement to work center 3 (recall that it completed at work center 2 at time 136525.90). As noted in the log, “scan batching” (the same as read batching) was used, so time was not spent to scan transfer lot 1 of job 21 at its completion (time 141506.26). Instead, work center 3 looked for another transfer lot to process. Transfer lot 2 of job 21 was already in queue at work center 3. Because of the repetitive lots logic and the secondary dispatching rules used for this dissertation, there was no need to look at other transfer lots or other queues once a transfer lot had been found of the same type that was just processed at the work center, so the log file does not show any evaluation of transfer lots 1 and 2 of job 1 that were waiting to be moved to work center 3. Transfer lot 2 began processing at time 141506.26, and at time 146756.34, it finished. The two transfer lots for job 21 each took 10 seconds for scanning, and they finished at work center 3 at time 146776.34. Work center 3 then had to evaluate what to process next, and it considered transfer lot 1 of job 19 at work center 2 (which had an operation due date of 172060.19), versus transfer lot 1 of job 1 at work center 2 (which had an operation due date of 222663.24, much greater than for job 19). It should be noted that to improve performance and save disk space, the second transfer lot for jobs 1 and 19 are not examined by the system or shown in the log, because they will always have the same operation due date (and processing time) as the other transfer lots for the same job. Looking at the entries for time 146776.34, it can be seen that transfer lot 1 for job 19 had priority and began its setup at work center 3, whereas transfer lot 2 for job 19 and transfer lots 1 and 2 for job 1 were pulled from work center 2 to wait at work center 3. Processing began at work center 3 for transfer lot of job 1 at time 147776.34 and ended at 152383.23, when it was then scanned for 10 seconds. At time 152393.23, the repetitive lots logic caused lot 2 of job 19 to begin processing at work center 3 and end at 157000.12, before taking 10 seconds to scan. At 157010.12, the first transfer lot of job 1 could finally begin processing at work center 3. The discussion in this paragraph illustrated the correct functionality for scan batching, repetitive lots logic, and use of the ODD priority rule.

Looking at Figure 21, which was created from the TLCompletion file, we see that transfer lot 1 of job 1 completed its last operation at time 162629.88, and transfer lot 2 completed its last operation at time 167249.65; both of these times are congruent with the results seen in Figure 19 from the QueueProcessing log file. The job due date was 222663.24, which was congruent with the JobCreation information seen in Figure 14. When transfer lot 1 completed, the "trailing job step" was 8, because transfer lot 2 was at work center 3 for operation 8 at that time (if there had been three transfer lots, and transfer lot 3 was still at work center 7 for operation 1, the trailing job step would be 1). The "Trailing Transfer Lot" cell was 0 (computer code for "false") because transfer lot 1 was *not* the trailing transfer lot; when transfer lot 2 completed, the "Trailing Transfer Lot" cell was -1 (computer code for "true") because it was the trailing transfer lot. The "LastTLForJob" cell is computed differently, but should always be the same value as the "Trailing Transfer Lot" cell in the same row. Storing both codes despite the fact that their values are expected to be the same provides another means of verifying that the logic in the system is consistently working as anticipated, because each code depends on different functionality in the simulation. When transfer lot 1 completed, transfer lot 2 still needed to be processed, so its “TLs Remaining” cell was 1; when transfer lot 2 completed, there were no more transfer lots left to be processed for job 1, so its “TLs Remaining” cell was 0. The number of transfer lots originally created each job was recorded in the last cell of each row. The discussion in this paragraph illustrates the congruency between the log files and the correct recording of transfer lot and job completions.

J#	TL#	E#	Completion Date	Due Date	Trailing Job Step	Trailing Transfer Lot	LastTLForJob	TLs Remaining	TLs Created
2	1	7	23558.59	58165.65	2	0	0	1	2
2	2	8	28256.49	58165.65	3	-1	-1	0	2
3	1	10	36371.11	146297.5	5	0	0	1	2
6	1	18	40798.56	81384.83	2	0	0	1	2
3	2	11	41272.46	146297.5	6	-1	-1	0	2
6	2	19	45696.78	81384.83	3	-1	-1	0	2
8	1	22	51688.89	89117.05	2	0	0	1	2
5	1	16	54641.92	78683.26	2	0	0	1	2
8	2	23	56802.24	89117.05	3	-1	-1	0	2
11	1	19	59061.42	78211.72	1	0	0	1	2
5	2	17	60075.39	78683.26	3	-1	-1	0	2
11	2	15	63474	78211.72	2	-1	-1	0	2
12	1	16	68905.42	82177.03	1	0	0	1	2
10	1	18	70623.75	103077.61	2	0	0	1	2
12	2	23	73304.79	82177.03	2	-1	-1	0	2
10	2	11	76149.57	103077.61	3	-1	-1	0	2
15	1	10	79170.8	96821.82	1	0	0	1	2
15	2	16	84036.81	96821.82	2	-1	-1	0	2
7	2	20	91047.05	170561.16	5	0	0	1	2
14	1	27	91418.04	141224.3	3	0	0	1	2
7	1	3	95564.01	170561.16	6	-1	-1	0	2
4	1	13	96220.99	182292.53	6	0	0	1	2
14	2	28	96291.55	141224.3	4	-1	-1	0	2
4	2	14	101786.4	182292.53	7	-1	-1	0	2
18	1	12	105817.47	141900.14	2	0	0	1	2
18	2	29	110563.43	141900.14	3	-1	-1	0	2
9	1	25	123377.02	238443.46	7	0	0	1	2
9	2	26	128677.85	238443.46	8	-1	-1	0	2
22	1	29	136016.02	156684.61	1	0	0	1	2
22	2	11	140808.16	156684.61	2	-1	-1	0	2
20	1	13	142391.08	225799.03	4	0	0	1	2
20	2	28	146941.31	225799.03	5	-1	-1	0	2
27	1	20	154641.49	175162.41	1	0	0	1	2
17	1	24	159417.07	284753.09	7	0	0	1	2
27	2	35	159428.26	175162.41	2	-1	-1	0	2
1	**1**	**4**	**162629.88**	**222663.24**	**8**	**0**	**0**	**1**	**2**
17	2	10	165032.76	284753.09	8	-1	-1	0	2
1	**2**	**5**	**167249.65**	**222663.24**	**9**	**-1**	**-1**	**0**	**2**

Figure 21. Information from a TLCompletion log file

In summary, careful examination (far beyond what was discussed here) of the substantial amount of information from all three log files indicates that the simulation model works correctly. The simulation logic and results are what is to be expected based on the various settings.

4.4. Verification of input parameters

This sub-section describes some of the verification of the functionality associated with the input parameters. Refer to Figure 6 - Figure 9 for visual context of how these factors are actually specified within the interactive simulation.

Number of Work Centers in Shop: This was held constant at eight work centers for the dissertation. Looking at the Arena reports, each of the eight work centers had nearly the same mean utilization, which implies that the logic to allocate operations to work centers was working properly.

Mean Interarrival Time: The mean interarrival time was computed as

$$\frac{\left[\left(\mathit{Mean\ Units\ Per\ Job} \times \mathit{Expected\ Operation\ Time}\right) + \mathit{Setup\ Time}\right] \times \mathit{Mean\ \#\ of\ Routing\ Operations}}{\mathit{Expected\ Utilization} \times \mathit{Number\ of\ Work\ Centers}}$$

As can be seen by the above equation, the mean arrival time does not directly change based on the mean scan time. The mean interarrival time was set based on an 80 percent utilization rate with instantaneous scanning, and then the same mean interarrival time was used for the other tracking method (TM) levels. The result is that the expected utilization when bar coding was used (TM2-TM5) was slightly higher than 80 percent.

Expected Basic Utilization: The expected basic utilization was computed based on the formula:

$$\frac{\left[\left(Expected\ Operation\ Time \times Units\ Per\ Job\right) + Setup\ Time + \left(Mean\ Scan\ Time \times \#\ of\ Transfer\ Lots\right)\right] \times Mean\ Number\ of\ Routing\ Operations}{Mean\ Inter-Arrival\ Time \times Number\ of\ Work\ Centers}$$

As can be seen by the above formula, the mean scan time is used to compute the expected utilization. The expected utilization was compared to the mean instantaneous utilization in Arena for each of the work centers. Each of the mean instantaneous utilizations was approximately equal to the expected utilizations and to each other.

Due Date Allowance Factor: The value specified for this factor is used with the total work content (setup, processing, and scan times) to determine operation and job due dates for each of the jobs (Baker, 1984). As expected, using a larger factor resulted in fewer tardy orders. Also, as noted elsewhere (e.g., the discussion for Figure 14), sample due dates were manually calculated and compared to the due dates written to the logs.

# of Different Job Types (0 if Each Is Unique): Because an open shop was modeled, this parameter was set to 0. Examination of the JobCreation log file showed that each of the jobs was unique.

Apply "Repetitive Lots" Logic: The on-screen setting chosen was “RL (Anywhere where valid TL)”, which means that the repetitive lots (RL) logic was used to look for transfer lots (TLs) of the same job type that were already in a queue immediately front of a work center *or* waiting to be pulled from a queue after another work center. In another words, the repetitive lots logic was applied to waiting transfer lots even if they were not immediately in queue in front of an idle work center, so long as they were available to be pulled from an upstream work center. Figure 22 demonstrates an example of the verification of the repetitive lots logic. At time 64190.14, transfer lot 2 for job 5 finished processing at work center 3. Its next processing step would take place at work center 8, but because work center 8 was busy, transfer lot 2 remained in queue after work center 3. At time 65543.7, transfer lot 1 of job 7 arrived at work center 8, but work center 8 was still busy. At time 66450.86, transfer lot 1 of job 5 was done processing and being scanned at work center 8. Work center 8 had to choose a new transfer lot to process. It chose transfer lot 2 for job 5, even though it was waiting in a queue after work center 3, because it wanted to avoid the additional setup time that would be required if it chose transfer lot 1 of job 7 next (even though it was already at work center 8). Similarly, at time 69129.39, transfer lot 3 for job 5 was chosen over transfer lot 1 for job 7, even though transfer lot 7 for job 1 had been waiting longer. The logic of both of these logged decisions shows that the repetitive lots logic was implemented correctly (e.g., in conjunction with the pull material movements logic and superseding the secondary dispatching rules logic).

64180.14	CWC: 3	NWC: 8	E#: 10	J#: 5	TL #: 2	We will scan 1 transfer lots, taking a time of 10
64190.14	CWC: 3	NWC: 8	E#: 10	J#: 5	TL #: 2	Done processing for type 5, about to release and move to WC 8
64190.14	CWC: 3	NWC: 8	E#: 10	J#: 5	TL #: 2	Will wait in queue after resource 3 for job step 2; TJS: 1 TTL: 0 Count(2): 25 Count(3): 50
64190.14	CWC: 3	NWC: 8	E#: 4	J#: 5	TL #: 3	Arriving at an idle resource for job step 2; TJS: 1 TTL: 0 Count(2): 25 Count(1): 25
64190.14	CWC: 3	NWC: 8	E#: 4	J#: 5	TL #: 3	Beginning 25 units in the TL. Actual process time for TL: 1407.82 Actual completion of last unit: 65597.96

. . .

65597.96	CWC: 3	NWC: 8	E#: 4	J#: 5	TL #: 3	We will scan 1 transfer lots, taking a time of 10
65607.96	CWC: 3	NWC: 8	E#: 4	J#: 5	TL #: 3	Done processing for type 5, about to release and move to WC 8
65607.96	CWC: 3	NWC: 8	E#: 4	J#: 5	TL #: 3	Will wait in queue after resource 3 for job step 2; TJS: 2 TTL: 0 Count(2): 25 Count(3): 75

. . .

65543.7	CWC: 8	NWC: 2	E#: 16	J#: 7	TL #: 1	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100

. . .

66440.86	CWC: 8	NWC: 1	E#: 9	J#: 5	TL #: 1	We will scan 1 transfer lots, taking a time of 10
66450.86	CWC: 8	NWC: 1	E#: 9	J#: 5	TL #: 1	Done processing for type 5, about to release and move to WC 1

E#: 16 J#: 7 TL #: 1 Type: 7 Step: 1 WC: 8 Op O DD: 119284.34 Op Exp Time for TL: 3437.03 BRM:65543.7 FCFS: 65543.7
E#: 10 J#: 5 TL #: 2 Type: 5 Step: 3 WC: 3 Op O DD: 187223.69 Op Exp Time for TL: 2678.53 BRM:64190.14 FCFS: 64190.14
Best is E#: 10 J#: 5 TL #: 2

69119.39	CWC: 8	NWC: 1	E#: 10	J#: 5	TL #: 2	We will scan 1 transfer lots, taking a time of 10
69129.39	CWC: 8	NWC: 1	E#: 10	J#: 5	TL #: 2	Done processing for type 5, about to release and move to WC 1

E#: 16 J#: 7 TL #: 1 Type: 7 Step: 1 WC: 8 Op O DD: 119284.34 Op Exp Time for TL: 3437.03 BRM:65543.7 FCFS: 65543.7
E#: 4 J#: 5 TL #: 3 Type: 5 Step: 3 WC: 8 Op O DD: 187223.69 Op Exp Time for TL: 2678.53 BRM:65607.96 FCFS: 65607.96
Best is E#: 4 J#: 5 TL #: 3

Figure 22. Information from a QueueProcessing log file that demonstrates repetitive lots logic

Dispatching rule: The experimental design for this dissertation had factor levels of the shortest processing time (SPT) rule, earliest due date per operation (ODD) rule, and first-come, first-served (FCFS) rule. These rules were applied when the repetitive lots logic could not find another transfer lot to process of the same job type as was most recently processed at a newly idle work center.

Figure 23 demonstrates the SPT rule. At time 19991.61, transfer lot 4 of job 1 finished at work center 6. There were no more transfer lots for job 5 to process there, so the repetitive lots logic did not come into play in this instance. The processing time at work center 6 for transfer lot 1 of job 3 was 4586.18. The processing time at work center 6 for transfer lot 1 of job 2 was 2885.81, so it was correctly chosen next for processing at work center 6.

19981.61	CWC: 6	NWC: 5	E#: 7	J#: 1	TL #: 4	We will scan 1 transfer lots, taking a time of 10
19991.61	CWC: 6	NWC: 5	E#: 7	J#: 1	TL #: 4	Done processing for type 1, about to release and move to WC 5

E#: 14 J#: 3 TL #: 1 Type: 3 Step: 1 WC: 6 Op O DD: 82560.08 **Op Exp Time for TL: 4586.18** BRM:4586.18 **SPT: 4586.18**
E#: 9 J#: 2 TL #: 1 Type: 2 Step: 2 WC: 4 Op O DD: 114388.63 **Op Exp Time for TL: 2885.81** BRM:2885.81 **SPT: 2885.81**
Best is E#: 9 J#: 2 TL #: 1

Figure 23. Information from a QueueProcessing log file that demonstrates SPT dispatching rule

The correct processing of the ODD rule was shown in Figure 17. At time 53970.07, after transfer lot 2 completed processing, work center 5 needed to compare transfer lot 1 of job 10 (which was waiting to be pulled from work center 6), versus transfer lot 1 of job 4 (which was waiting to be pulled from work center 7). Because the operation due date for the job 10 was 103077.61, while 101000.68 for job 4, job 4 was correctly chosen.

Figure 24 demonstrates the FCFS rule. At time 65543.7, transfer lot 1 of job 7 arrived at work center 8, but it had to wait until the transfer lots for job 5 were done processing (this is not directly shown in the figure, but can be seen by examining the full log file). At time 72238.32, transfer lot 1 of job 6 completed processing at work center 5, but waited in queue after work center 5 because work center 8 (its next step) was still busy with job 5. At time 74486.45, transfer lot 4 for job 5 finished at work center 8, and there were no more transfer lots for job 5 to process there, so the repetitive lots logic does not come into play in this instance. Because transfer lot 1 for job 7 had been waiting since 65543.7 (compared to transfer lot 1 for job 6, which had been waiting since 72238.32), transfer lot 1 for job 7 was correctly chosen.

65543.7	CWC: 8	NWC: 2	E#: 16	J#: 7	TL #: 1	Arriving at a busy resource for job step 1; will wait in queue; TJS: 1 TTL: 0 Count(1): 100

. . .

72238.32	CWC: 5	NWC: 8	E#: 2	J#: 6	TL #: 1	Done processing for type 6, about to release and move to WC 8
72238.32	CWC: 5	NWC: 8	E#: 2	J#: 6	TL #: 1	Will wait in queue after resource 5 for job step 2; TJS: 1 TTL: 0 Count(2): 0 Count(3): 25

. . .

74476.45	CWC: 8	NWC: 1	E#: 12	J#: 5	TL #: 4	We will scan 1 transfer lots, taking a time of 10
74486.45	CWC: 8	NWC: 1	E#: 12	J#: 5	TL #: 4	Done processing for type 5, about to release and move to WC 1

E#: 16 J#: 7 TL #: 1 Type: 7 Step: 1 WC: 8 Op O DD: 119284.34 Op Exp Time for TL: 3437.03 BRM:65543.7 FCFS: 65543.7
E#: 2 J#: 6 TL #: 1 Type: 6 Step: 3 WC: 5 Op O DD: 228654.4 Op Exp Time for TL: 3598.59 BRM:65543.7 FCFS: 72238.32
Best is E#: 16 J#: 7 TL #: 1

Figure 24. Information from a QueueProcessing log file that demonstrates FCFS dispatching rule

Product units per job: This is relatively easily verified by examining the logs.

Operations per job: This logic has been verified by looking at the log files and comparing the actual utilization to the expected utilization.

Each WC Only Appears Once Per Routing: Selecting this option means that each work center (WC) will appear at most only once per routing for each job type. Examination of the JobCreation log file verified that this logic works correctly.

Mean Setup Time Per Operation: Examination of the QueueProcessing log file verified that the logic works correctly.

Processing Time Per Unit Per Operation: Examination of the JobCreation log file verified that this logic works correctly.

Mean Scan Time Per Unit Per Operation: Examination of the QueueProcessing log file verified that this logic works correctly. As expected, pilot runs showed that increasing scan times resulted in worse performance.

Lot Streaming: Static lot streaming (using a fixed number of transfer lots per job) was used for this dissertation (as opposed to dynamically splitting lots based on system criteria).

Push or Pull: Transfer lots moved between work centers based on pull logic that was verified by examination of the QueueProcessing log file and observing the graphical interface.

Static # of Transfer Lots in Addition to Any Flag Lot: This was set based on the experimental design factor levels. It was verified by examining the QueueProcessing and

TLCompletion log files and observing the graphical interface. As expected, pilot runs showed that increasing the number of transfer lots improved most of the performance measures, but at the expense of more material movements.

% of Original Lot in Transfer Lot #1, % of Original Lot in Transfer Lot #2, % of Original Lot in Transfer Lot #3, % of Original Lot in Transfer Lot #4: Only the functionality of the first two of these fields was used by the dissertation, when 2 transfer lots of 50 units were used. When more than 4 transfer lots were used, the percent of each job allocated to each transfer lot was simply a direct division based on the number of transfer lots and not these form fields.

% Probability of Batching a Read: This was verified by examining the QueueProcessing log and reports from Arena. One can scan through the QueueProcessing log for the verbiage "We will scan this transfer lot later." When the next transfer lot is scanned, the time needed for scanning proportionally takes longer, because the batched transfer lots also need to be scanned.

In Figure 25, transfer lot 2 for job 9 finished processing at time 106534.45 at work center 4. The next location where it would be processed was at work center 1, but because of the pull logic and the operator decided not to scan it, it remained at work center 4. Transfer lot 3 for job 9 then began production at work center 4. At time 107216.83, work center 1 finished processing transfer lot 1 for job 9. Normally, transfer lot 2 for job 9 would then be pulled from work center 4, but because it had not yet been scanned, work center 1 was not aware that it was ready to be moved. Work center 1 remained unnecessarily idle until time 107770.37, when transfer lot 1 for job 17 was able to utilize it. Because it was a different job type, though, processing job 17 resulted in a new setup being performed at work center 1, essentially wasting its capacity. At time 108720.19, transfer lot 4 for job 9 finished at work center 4, and both transfer lot 3 and transfer lot 4 were scanned, thus making them available for processing at work center 1. It was not until time 129240.75, though, that transfer lots 3 and 4 for job 9 finally moved to work center 1, because other transfer lots with higher priority needed the capacity (including the other transfer lots of job 17).

106534.45	**CWC: 4**	**NWC: 1**	E#: 13	**J#: 9**	**TL #: 2**	**We will scan this transfer lot later.**
106534.45	CWC: 4	NWC: 1	E#: 13	J#: 9	TL #: 2	Done processing for type 9, about to release and move to WC 1
106534.45	CWC: 4	NWC: 1	E#: 13	J#: 9	TL #: 2	**Will wait in queue after resource 4** for job step 4; TJS: 4 TTL: 0 Count(4): 60 Count(5): 40
106534.45	CWC: 4	NWC: 1	E#: 38	**J#: 9**	**TL #: 3**	Beginning 20 units in the TL. Actual process time for TL: 2185.74 Actual completion of last unit: 108720.19

...

107216.83	**CWC: 1**	NWC: 5	E#: 21	**J#: 9**	**TL #: 1**	Done processing for type 9, about to release and move to WC 5

There was nothing else already completed to select for processing now here at WC 1

...

107770.37	**CWC: 1**	NWC: 6	E#: 42	**J#: 17**	**TL #: 1**	**Arriving at an idle resource** for job step 4; TJS: 2 TTL: 0 Count(4): 20 Count(3): 20
107770.37	CWC: 1	NWC: 6	E#: 42	J#: 17	TL #: 1	Resource seized. Different type or step than previously at WC, **new setup of 1000**.Completion for setup at 108770.37.

...

108720.19	**CWC: 4**	NWC: 1	E#: 38	**J#: 9**	**TL #: 3**	**We will scan 2 transfer lots, taking a time of 20**
108740.19	CWC: 4	NWC: 1	E#: 38	J#: 9	TL #: 3	Done processing for type 9, about to release and move to WC 1
108740.19	CWC: 4	NWC: 1	E#: 38	**J#: 9**	**TL #: 3**	**Will wait in queue after resource 4** for job step 4; TJS: 4 TTL: 0 Count(4): 40 Count(5): 40

...

129240.75	**CWC: 1**	NWC: 5	E#: 13	**J#: 9**	**TL #: 2**	**Arriving at an idle resource** for job step 5; TJS: 5 TTL: 0 Count(5): 80 Count(4): 0
129240.75	CWC: 1	NWC: 5	E#: 13	J#: 9	TL #: 2	Resource seized. Different type or step than previously at WC, new setup of 1000.Completion for setup at 130240.75.
129240.75	CWC: 1	NWC: 5	E#: 38	J#: 9	TL #: 3	Arriving at a busy resource for job step 5; will wait in queue; TJS: 5 TTL: 0 Count(5): 80 Count(4): 0
129240.75	CWC: 1	NWC: 5	E#: 39	J#: 9	TL #: 4	Arriving at a busy resource for job step 5; will wait in queue; TJS: 5 TTL: 0 Count(5): 80 Count(4): 0
129240.75	CWC: 1	NWC: 5	E#: 40	J#: 9	TL #: 5	Arriving at a busy resource for job step 5; will wait in queue; TJS: 5 TTL: -1 Count(5): 80 Count(4): 0

Figure 25. Information from a QueueProcessing log file that demonstrates scan batching functionality

4.5. Comparison of simulation results to earlier studies

By replicating results from earlier studies, credibility and validity for the rest of the dissertation simulation results are enhanced (Law and Kelton, 2000). Results relevant to the below discussion will be discussed in more detail in the following chapter, but even in the form seen in this chapter, the results provide further support for the simulation model's verification and validation.

The flexibility of the simulation model design for this dissertation allowed for comparisons to the job shop configurations used by Baker and Kanet (1983). As seen in Figure 26 , the proportion tardy measurements were very similar for 80 percent utilization and various levels of due date tightness when using the SPT and ODD dispatching rules. Some variation is to be expected because of the stochastic nature of the shop being modeled, and because the exact conditions of those papers could not be precisely duplicated. For example, Baker and Kanet (1983) pre-loaded their shop with 64 jobs, but did not provide information about the exact nature of those jobs. Furthermore, the exponential distribution used for interarrival times has a relatively high coefficient of variation (CV), which leads to high variation that is difficult to exactly duplicate. Baker and Kanet (1983) only used one replication per treatment, taking the 501st through 5500th job within each run for each treatment. For the dissertation's comparison with Baker and Kanet (1983), approximately 500 jobs were discarded for the warm-up period, and approximately 5000 jobs were included for the computation of proportion tardy. Together with the other verification and validation results seen in this chapter, the congruent results with Baker and Kanet (1983) supports the notion that the logic for utilization, due date tightness, tardiness, and the SPT and ODD dispatching rules was correctly designed and implemented.

	Baker and Kanet (1983)	Hozak Test	Baker and Kanet (1983)	Hozak Test
Due Date Tightness	Dispatching Rule			
K	SPT	SPT	ODD	ODD
2.5	0.486	0.476	0.803	0.791
5	0.096	0.090	0.163	0.130
7.5	0.036	0.037	0.029	0.030
10	0.020	0.022	0.014	0.016

Figure 26. Comparison of proportion tardy to Baker and Kanet (1983) for 80 percent utilization

Similar to the due date tightness "cross-over" effects for dispatching rules observed in Baker (1984), the SPT rule for the dissertation simulation performed relatively well (compared to the ODD and FCFS dispatching rules) for proportion tardy when due dates were tight, and relatively less well (compared to ODD) when due dates were loose. These results help verify and validate the design and implementation for the priority rules, due date setting, and performance reporting.

Baker (1984) did not consider lot streaming. In contrast, Jacobs and Bragg (1988) specifically examined lot streaming, and they also found that the SPT rule performed better than the FCFS rule. This dissertation research produced results compatible with those earlier findings. The results for this research were also compatible with the findings of Jacobs and Bragg (1988) that flow time performance improved with decreased transfer lot size, thus providing verification and validation for the use of those dispatching rules with lot streaming and varying sizes of transfer lots.

Similar to the lot streaming research of Wagner and Ragatz (1994), this research found that lot streaming (when not considering scan times) offered improvements in flow time and proportion tardy with increased number of transfer lots. In both sets of research, the performance improvements were achieved regardless of the magnitude of the setup time. Wagner and Ragatz specifically looked at the FCFS rule to develop their findings; this dissertation considered several dispatching rules, including FCFS, and found agreement with Wagner and Ragatz. The similar results provide verification and validation support for the basic lot streaming logic, the repetitive lots primary dispatching rule, and the FCFS secondary dispatching rule.

Diminishing returns for flow time performance in a job shop with increased number of transfer lots was also identified by Smunt et al. (1996). The comparable results provide further verification and validation support for the basic lot streaming logic, the repetitive lots primary dispatching rule, the reporting of flow time performance, and the FCFS secondary dispatching rule.

Kher et al. (2000) measured the pull material movements in a flow shop using lot streaming. Although this research focuses on job shops, the results are compatible in the sense that a doubling of the number of transfer lots per job results in less than twice as many material movements. The results of Kher et al. (2000), together with the intuitive expectation of reduced material movements from using pull flow, provides face validity (Law and Kelton, 2000) for this aspect of the simulation model results.

4.6. Results of real-world manufacturer duplicated in simulation model

The dissertation author worked closely with Navistar, a long-time user of RFID and manufacturer of trucks, buses, and engines. He replicated the performance of one of Navistar's processes by using the same Arena simulation software used for the dissertation. Confidentiality agreements prohibit disclosure of the simulation model for Navistar's production processes and use of RFID. Nonetheless, it is believed that familiarity with the issues experienced by a long-time user of RFID systems strengthens the validity and credibility of the rest of the RFID research that can be published by the author (Law and Kelton, 2000).

Navistar is an international company with many plants and annual sales of over ten billion dollars. A significant amount of its production is made to order, and it competes in part based on the customized options it offers. Based on the complexity of its processes throughout the plants, warehouses, and retail outlets in its deep supply chain, it is not surprising that traceability is often of high concern. Navistar's industry is known for its intense competitiveness, which highly motivates it to also improve inventory, cost, delivery, and quality performance. Its products often sell for tens of thousands of dollars per unit, and each plant may produce several hundred units per day. Navistar's processes include both linear and jumbled material flows.

Navistar had the following objectives for the RFID research project that they undertook with the dissertation author:

1. Understand RFID technology and how it should be applied in general.

2. Increase information technology (IT) readiness by identifying RFID standards and a framework for supporting a focused pilot.
3. Increase IT readiness by developing a non-biased decision matrix on when and how RFID should be applied to Navistar's processes based on theory and empirical evidence.
4. Collect business case studies and build credibility to promote RFID at Navistar for internal customer readiness.

Presentations and documents were periodically provided to managers and team members from both the IT and internal customer (e.g., operations) functions. Although Navistar managers had ideas about possible applications of the RFID technology beyond what was currently in place in their organization, it recognized that scientific standards have long suggested the need to invest the time to seek a wide range of input before developing hypotheses. Although there is no shortage of information on RFID, it is not always summarized well and cannot be considered to be neutral due to its dissemination by vendors who have much to gain from promoting implementations. Even the neutrality of industry analyst firms has been called into question because of their relationship with vendors (Stein, 1999; Caulfield, 2003).

Internal perception was also a concern. While the technical architecture leader had been investing time to stay current with RFID, there was concern that other functions would incorrectly perceive that the technology was being pushed on them. Use of the academic research team (the author and his advisor) from the operations management domain helped validate the jointly generated recommendations from a business perspective. Navistar also appreciated that papers submitted to academic journals and presented at conferences go through an independent review process.

Although there was some initial concern about the sharing of valuable insights from this research (much less proprietary or confidential information about Navistar processes), those were balanced by assurances that sensitive material would be disguised or omitted, papers could be reviewed by Navistar before submission, publication pipelines are long, and there might be significant internal and external marketing benefits for Navistar. As noted earlier, Navistar actually expects journal articles to be published as part of their arrangement with the author; besides providing validation of the analysis, published papers are expected to bring acclaim to the project and stimulate necessary executive and managerial support.   In short, both Navistar and the academic researchers have been motivated to support the work of each other.

Looking at the Navistar objectives discussed earlier, the goal of “readiness” is seen repeatedly. From an IT perspective, this involved understanding RFID capabilities, standards, trends, and associated ramifications. IT readiness also involved understanding related issues such as bar code co-existence, how information should be stored (e.g., centrally or distributed to the tags), and necessary personnel capabilities. From an internal customer perspective, attaining readiness involved evaluating potential sources of ROI, identifying ideal and necessary business conditions, prioritizing related requirements, and determining timing of pilots and larger implementations. Because funding for this project came from the IT function, technical concerns were considered, but because Navistar has a progressive view of IT, the business needs of the IT function’s internal customers were also vitally important. Navistar wanted the IT function to be able to quickly and effectively respond once its internal customers demanded RFID functionality. The author and his colleagues not only proactively developed this IT function readiness, but worked with internal customers to identify and share promising opportunities with them. Economist W. Brian Arthur (CIO Magazine, 2003) supports the idea that IT needs to help drive initiatives based on technological innovation: "If you're trained as an MBA, or a lawyer or a middle manager, you can't be expected to have the imagination to see what's possible—it's too complex. So I think it's going to be IT people showing top management what is possible."

The qualitative and quantitative research conducted for this dissertation research has helped show Navistar management what is possible by using RFID, and where and when it should be applied. Besides analyzing the existing use of RFID at Navistar, future opportunities were evaluated from strategic, operational, and technical perspectives. The success of the research has motivated both the author and Navistar to pursue further collaborative opportunities with each other.

CHAPTER 5

EXPERIMENTAL RESULTS AND DISCUSSION

This chapter is split into sub-sections corresponding to the hypotheses presented in Chapter 3. Each sub-section contains statistical results and discussion of the practical ramifications. The analysis develops strategic and tactical insights about RFID use, including identifying when RFID is most and least advantageous compared to data collection alternatives such as bar coding. The key statistical and managerial findings are summarized at the end of each sub-section. Before proceeding with the core analysis, the experimental design and analytical techniques are briefly reviewed.

Figure 27 reviews each of the experimental design factors that were originally discussed in Chapter 3. RFID technology provides instantaneous tracking. The technical process of bar coding is also very fast, but because line-of-sight is required, the product typically requires some sort of physical reorientation for appropriate visibility by the bar code scanner (Kärkkäinen, 2003). Studies have indicated that it can take 4-15 seconds on average for the scanning and labor associated with this orientation, even in relatively repetitive environments (Palmer, 1995; Barlow, 2005; Kinsella, 2005; Navistar, 2006; Sullivan, 2007; Gaukler and Hausman, under review). In less repetitive environments such as job shops, one might reasonably expect that it could take even longer for operators to stop what they are doing, scan the product, and then resume the rest of their processing. For example, Gaukler and Hausman (under review) performed two industrial studies and estimated scan times of 10-12 seconds on average, but asserted that the times could be substantially more if workers have to walk to the location of the object to be scanned.

Multi-Level Factor	Level Code	Level Description
Transfer lot tracking mechanism	TM1	RFID (Instantaneous read)
	TM2	Fast deterministic bar code (read takes 4 seconds)
	TM3	Slow deterministic bar code (read takes 10 seconds)
	TM4	Fast stochastic bar code (read time follows a gamma distribution with a mean of 4 seconds)
	TM5	Slow stochastic bar code (read time follows a gamma distribution with a mean of 10 seconds)
Read batching	RB1	Each read of each transfer lot occurs immediately after process completion at each work center
	RB2	1 percent of reads of eligible transfer lots batched
	RB3	2.5 percent of reads of eligible transfer lots batched
Number of transfer lots	NTL1	2 transfer lots of size 50 units each
	NTL2	5 transfer lots of size 20 units each
	NTL3	10 transfer lots of size 10 units each
	NTL4	20 transfer lots of size 5 units each
	NTL5	50 transfer lots of size 2 units each
Setup / processing time ratio	SPR1	10:100 (setup time is ~ 9 percent of setup + processing time for all units in the job)
	SPR2	50:100 (setup time is ~ 33 percent of setup + processing time for all units in the job)
	SPR3	100:100 (setup is 50 percent of setup + processing time for all units in the job)
Secondary dispatching rule	SDR1	FCFS (first come, first served)
	SDR2	SPT (shortest processing time)
	SDR3	ODD (earliest operation due date)
Coefficient of variation (CV) of processing time between work centers in routing	CV1	.07 (87.5 – 112.5 seconds / unit)
	CV2	.29 (50 – 150 seconds / unit)
Due date tightness	K1	2.5 times the total work content
	K2	5 times the total work content

Figure 27. Multi-level factors for experimental design

Besides requiring more time for positioning and scanning, bar code labels are also subject to smudging and other damage for which RFID is less susceptible (e.g., because the tags can be stored inside of products) (Kärkkäinen, 2003; Angeles, 2005; Global

Commerce Initiative and IBM, 2005). When a bar code label needs to be re-read and/or replaced, the tracking process can take much more than 10 seconds (Gaukler and Hausman, under review). In this case, the statistical distribution of the tracking process would have a long tail, as is possible with the gamma distribution.

Thus, the five TM levels seen in the table are used to reflect the time it takes for identifying a transfer lot when using:

- RFID technology is being used (instantaneous reads) (TM1)
- deterministically fast bar coding (four seconds per read) (TM2)
- deterministically slow bar coding (ten seconds per read) (TM3)
- stochastically fast bar coding (a gamma distribution with a mean read time of four seconds) (TM4)
- stochastically slow bar coding (a gamma distribution with a mean read time of ten seconds) (TM5).

Previous lot streaming research has not considered the time it takes to track products (i.e., this TM factor).

The read batching (RB) factor can be used to represent unreliable data collection, either because workers performing the bar code activity do not consistently record transfer lots as having completed processing at a work center (and thus downstream work centers will not know that material is available to be pulled), or because the RFID technology is relatively new and also may not reliably identify the completion of a transfer lot that is ready to be pulled. Thus, the time spent for the data collection activity (the TM factor) is modeled independently from the reliability of the transfer lot tracking mechanism process (the RB factor). Although the literature and interviews with industry managers provide examples of procedures that are not reliably followed by workers without some form of additional controls like RFID technology (Raman et al., 2001; Hill Jr., 2004; Tellkamp et al., 2004; Collins, 2006e; Gaukler and Hausman, under review), the impact of different levels of data collection process conformance on flow times and tardiness has never been modeled.

The number of lot transfer lots (NTL) factor corresponds to the extent of lot streaming used. Because the use of more transfer lots is synonymous with more lot streaming and smaller lot sizes, the use of more transfer lots can also be thought of as the extent of process changes. As has been discussed in the preceding chapters, compared to data collection alternatives such as bar coding (TM2-TM5), RFID (TM1) enables better traceability and control of the increased number of transfer lots (NTL) moving through the system. Thus, RFID facilitates process changes (higher NTL) that in turn are expected to contribute to improvements in mean flow time (MFT) and proportion of jobs tardy (PT). Although other process changes are certainly possible as a result of RFID (Hardgrave et al., 2005), the focus on the process change of using high levels of lot streaming that are not practical with bar coding was expected to result in relatively clear differentiation between RFID and bar coding performance. Furthermore, given that much of the RFID literature has posited that process changes are necessary to achieve significant improvement when using RFID (Byrnes, 2004; Murphy-Hoye et al., 2005; Sliwa, 2005b), the use of the lot streaming factor (NTL) allows comparison between the possible improvement when using RFID but not changing the process (TM1 and NTL1) versus using RFID to make increasingly more substantial process changes (TM1 and NTL2-NTL5).

The setup/processing time ratio (SPR) and coefficient of variation of processing time between work centers (CV) factors can be thought of as operating conditions, and the secondary dispatching rule (SDR) and due date tightness parameter (K) can be thought of as operating policies. The terms “operating conditions and policies” were used by Kher et al. (2000), who called for more varieties of conditions and policies to be included as model factors in related future lot streaming research (as noted in Chapter 3, this dissertation accomplishes that). An “operating condition” is a characteristic of the circumstances under which a manufacturer operates (e.g., because of its chosen product lines and processes), whereas as an “operating policy” is a decision rule used by the manufacturer. By comparing current operating conditions to the conditions shown to be appropriate for RFID use, companies can make better decisions about whether to invest in RFID or use a less expensive and complex data collection alternative. Similarly, companies that choose to use RFID will want to know if there are operating policies that can be used to maximize the value of their technology.

The ANOVA statistics for the mean flow time (MFT), proportion of tardy jobs (PT), and total material movements (MM) dependent variables are shown in Figure 28, Figure 29, and Figure 30, respectively. As noted in Chapter 3, one of the key assumptions of using repeated measures (within-groups) ANOVA is sphericity. Sphericity refers to the equality of variances of the *differences* between treatment levels. The sphericity assumption is a less restrictive form of the homogeneity of variance assumption (that requires equal variances across conditions) in between-groups ANOVA designs (Field, 2005: 428). SPSS can compute "epsilon" values via several different methods to estimate the sphericity of the data. The degrees of freedom are multiplied by the epsilon values to obtain adjusted degrees of freedom that can be used to more accurately evaluate each ANOVA F statistic. Epsilon values closer to 1 represent data that are more spherical (and thus are better than lower values because they come closer to meeting the repeated measures ANOVA assumption and lead to less of a reduction in the degrees of freedom). The application of the epsilon estimate defined by Greenhouse and Geisser (1959) is appropriate for conservative analysis (Barcikowski and Robey, 1984; Girden, 1992: 19-21). Thus, the degrees of freedom and p-values in Figure 28 - Figure 30 have been corrected based on the Greenhouse-Geisser epsilon estimates.

Source	Type III Sum of Squares	Greenhouse-Geisser Estimate of Epsilon	Corrected df	Mean Square	F	Significance
TM	2.9503E+11	0.253	1.01	2.9110E+11	120.06	0.000 ***
RB	1.6171E+08	0.747	1.49	1.08272E+08	29.28	0.000 ***
NTL	6.8295E+11	0.271	1.08	6.3046E+11	111.05	0.000 ***
SPR	5.6536E+13	0.637	1.27	4.4406E+13	123.53	0.000 ***
SDR	8.9534E+11	0.754	1.51	5.93563E+11	84.63	0.000 ***
CV	3.6069E+10	1.000	1.00	3.6069E+10	17.83	0.002 **
K	2.2970E+10	1.000	1.00	2.2970E+10	41.76	0.000 ***
TM * RB	2.0396E+07	0.459	3.68	5.54954E+06	0.56	0.679
TM * NTL	3.4674E+11	0.067	1.07	3.2402E+11	94.49	0.000 ***
TM * SPR	4.5840E+08	0.236	1.89	2.4259E+08	1.21	0.321
TM * SDR	1.0763E+09	0.310	2.48	4.3443E+08	7.52	0.002 **
TM * CV	2.7097E+07	0.607	2.43	1.11586E+07	0.30	0.782
TM * K	2.4252E+07	0.414	1.65	1.4655E+07	3.72	0.056 †
RB * NTL	3.7035E+07	0.492	3.93	9.41367E+06	1.26	0.305
RB * SPR	3.3301E+07	0.625	2.50	1.33188E+07	1.70	0.201
RB * SDR	1.3858E+07	0.506	2.02	6.8485E+06	0.80	0.465
RB * CV	3.0566E+05	0.857	1.71	1.78237E+05	0.05	0.926
RB * K	1.9204E+02	0.939	1.88	1.02270E+02	0.00	0.999
NTL * SPR	5.4474E+09	0.277	2.22	2.4572E+09	5.52	0.011 *
NTL * SDR	1.1778E+09	0.390	3.12	3.7735E+08	2.58	0.071 †
NTL * CV	6.6012E+09	0.617	2.47	2.67424E+09	36.01	0.000 ***
NTL * K	1.3000E+08	0.422	1.69	7.7078E+07	4.14	0.042 *
SPR * SDR	2.1396E+10	0.636	2.54	8.4134E+09	4.98	0.011 *
SPR * CV	7.2006E+10	0.669	1.34	5.3803E+10	59.69	0.000 ***
SPR * K	1.6949E+09	0.627	1.25	1.3506E+09	7.01	0.018 *
SDR * CV	1.6969E+11	0.582	1.16	1.4570E+11	122.78	0.000 ***
SDR * K	4.5939E+10	0.500	1.00	4.5939E+10	41.76	0.000 ***
CV * K	3.3569E+05	1.000	1.00	3.3569E+05	0.00	0.950
TM * RB * NTL	1.3745E+08	0.146	4.67	2.9426E+07	0.94	0.458
TM * RB * SPR	6.9123E+07	0.299	4.79	1.4429E+07	0.96	0.452
TM * RB * SDR	4.1164E+07	0.307	4.91	8.3838E+06	0.82	0.542
TM * RB * CV	5.4249E+07	0.417	3.33	1.6278E+07	0.92	0.451
TM * RB * K	1.1770E+06	0.382	3.06	3.8477E+05	0.85	0.482
TM * NTL * SPR	1.0370E+09	0.081	2.60	3.9884E+08	1.23	0.319
TM * NTL * SDR	1.7170E+09	0.101	3.24	5.2920E+08	3.46	0.026 *
TM * NTL * CV	1.2680E+08	0.232	3.72	3.4104E+07	0.60	0.655
TM * NTL * K	2.4479E+07	0.267	4.28	5.7198E+06	1.75	0.155
TM * SPR * SDR	2.1711E+08	0.326	5.21	4.1639E+07	2.07	0.084 †
TM * SPR * CV	6.5225E+07	0.356	2.85	2.2877E+07	0.59	0.621
TM * SPR * K	9.7373E+06	0.492	3.93	2.4760E+06	1.16	0.346
TM * SDR * CV	1.3579E+08	0.452	3.62	3.7517E+07	1.52	0.223
TM * SDR * K	4.8505E+07	0.207	1.65	2.9311E+07	3.72	0.056 †
TM * CV * K	6.3032E+06	0.542	2.17	2.9052E+06	1.76	0.197
RB * NTL * SPR	7.1167E+07	0.309	4.94	1.4400E+07	1.03	0.413
RB * NTL * SDR	7.1616E+07	0.264	4.22	1.6975E+07	1.12	0.363
RB * NTL * CV	2.5697E+07	0.368	2.95	8.7183E+06	0.71	0.554
RB * NTL * K	4.2377E+05	0.483	3.87	1.09601E+05	0.35	0.834
RB * SPR * SDR	5.6796E+07	0.318	2.54	2.2325E+07	1.49	0.247
RB * SPR * CV	1.1689E+07	0.499	1.99	5.8616E+06	0.41	0.667
RB * SPR * K	9.2007E+05	0.554	2.22	4.15300E+05	0.84	0.458
RB * SDR * CV	1.1087E+07	0.590	2.36	4.6993E+06	0.53	0.624
RB * SDR * K	3.8407E+02	0.469	1.88	2.0454E+02	0.00	0.999
RB * CV * K	1.0464E+05	0.725	1.45	7.21799E+04	0.26	0.707
NTL * SPR * SDR	1.1065E+09	0.281	4.50	2.4612E+08	2.02	0.103
NTL * SPR * CV	1.1282E+09	0.420	3.73	3.02510E+08	4.82	0.004 **
NTL * SPR * K	4.5404E+07	0.381	3.05	1.4898E+07	1.16	0.343
NTL * SDR * CV	1.1282E+09	0.466	3.73	3.0251E+08	4.82	0.004 **
NTL * SDR * K	2.6000E+08	0.211	1.69	1.5416E+08	4.14	0.042 *
NTL * CV * K	2.3770E+07	0.410	1.64	1.4502E+07	1.71	0.217
SPR * SDR * CV	6.2835E+09	0.562	2.25	2.7970E+09	17.39	0.000 ***
SPR * SDR * K	3.3898E+09	0.314	1.25	2.7013E+09	7.01	0.018 *
SPR * CV * K	1.7017E+07	0.641	1.28	1.3272E+07	0.33	0.630
SDR * CV * K	6.7139E+05	0.500	1.00	6.7139E+05	0.00	0.950

***, **, *, and † indicate significance at α=.001, .01, .05, and .10, respectively

Figure 28. Mean Flow Time (MFT): Repeated Measures ANOVA Tests of Within-Subjects Effects

Source	Type III Sum of Squares	Greenhouse-Geisser Estimate of Epsilon	Corrected df	Mean Square	F	Significance
TM	1.3212E+00	0.259	1.03	1.2771E+00	126.66	0.000 ***
RB	7.2731E-04	0.872	1.74	4.1719E-04	13.99	0.000 ***
NTL	3.4668E+00	0.378	1.51	2.2938E+00	155.20	0.000 ***
SPR	3.9261E+00	0.901	1.80	2.1790E+00	3.14	0.075 †
SDR	2.9554E+01	0.529	1.06	2.7938E+01	38.27	0.000 ***
CV	4.4157E-01	1.000	1.00	4.4157E-01	23.32	0.001 ***
K	5.3668E+02	1.000	1.00	5.3668E+02	287.03	0.000 ***
TM * RB	2.7879E-04	0.532	4.25	6.5537E-05	0.82	0.528
TM * NTL	1.5697E+00	0.071	1.14	1.3827E+00	105.81	0.000 ***
TM * SPR	8.2108E-02	0.290	2.32	3.5353E-02	54.67	0.000 ***
TM * SDR	1.0559E-01	0.233	1.87	5.6527E-02	29.40	0.000 ***
TM * CV	1.1812E-04	0.625	2.50	4.7287E-05	0.21	0.858
TM * K	3.5453E-01	0.258	1.03	3.4326E-01	91.99	0.000 ***
RB * NTL	3.5443E-04	0.460	3.68	9.6384E-05	1.20	0.327
RB * SPR	2.5988E-04	0.501	2.00	1.2973E-04	3.18	0.066 †
RB * SDR	3.0769E-05	0.734	2.94	1.0475E-05	0.31	0.812
RB * CV	2.7886E-05	0.804	1.61	1.7346E-05	0.44	0.611
RB * K	3.2433E-04	0.693	1.39	2.3416E-04	5.98	0.022 *
NTL * SPR	9.6979E-02	0.380	3.04	3.1891E-02	21.37	0.000 ***
NTL * SDR	3.6368E-01	0.335	2.68	1.3564E-01	42.21	0.000 ***
NTL * CV	2.5488E-02	0.729	2.92	8.7355E-03	23.62	0.000 ***
NTL * K	2.1915E+00	0.298	1.19	1.8410E+00	180.30	0.000 ***
SPR * SDR	1.4455E-01	0.502	2.01	7.1951E-02	1.03	0.377
SPR * CV	5.5569E-01	0.642	1.28	4.3255E-01	42.76	0.000 ***
SPR * K	1.7063E+00	0.978	1.96	8.7270E-01	3.93	0.040 *
SDR * CV	2.2044E+00	0.616	1.23	1.7880E+00	246.51	0.000 ***
SDR * K	4.0822E+01	0.522	1.04	3.9094E+01	86.02	0.000 ***
CV * K	2.9558E-01	1.000	1.00	2.9558E-01	23.33	0.001 ***
TM * RB * NTL	1.0931E-03	0.198	6.34	1.7240E-04	0.92	0.490
TM * RB * SPR	3.4320E-04	0.365	5.84	5.8759E-05	0.69	0.659
TM * RB * SDR	5.9356E-04	0.292	4.67	1.2716E-04	1.35	0.263
TM * RB * CV	2.8688E-04	0.447	3.58	8.0200E-05	0.93	0.451
TM * RB * K	2.9381E-04	0.509	4.07	7.2145E-05	1.31	0.285
TM * NTL * SPR	1.0217E-01	0.180	5.76	1.7750E-02	27.12	0.000 ***
TM * NTL * SDR	1.3746E-01	0.085	2.73	5.0439E-02	23.52	0.000 ***
TM * NTL * CV	1.0818E-03	0.202	3.23	3.3513E-04	0.78	0.525
TM * NTL * K	3.7147E-01	0.082	1.30	2.8475E-01	69.76	0.000 ***
TM * SPR * SDR	1.4788E-02	0.317	5.08	2.9118E-03	13.62	0.000 ***
TM * SPR * CV	1.0735E-03	0.503	4.02	2.6674E-04	1.56	0.206
TM * SPR * K	2.6624E-02	0.319	2.55	1.0426E-02	30.66	0.000 ***
TM * SDR * CV	1.0138E-03	0.482	3.86	2.6278E-04	1.52	0.220
TM * SDR * K	8.7926E-02	0.241	1.93	4.5634E-02	34.85	0.000 ***
TM * CV * K	5.6842E-04	0.451	1.80	3.1496E-04	1.67	0.220
RB * NTL * SPR	6.4245E-04	0.318	5.09	1.2628E-04	1.10	0.372
RB * NTL * SDR	3.9671E-04	0.342	5.47	7.2468E-05	0.71	0.630
RB * NTL * CV	1.2569E-04	0.427	3.42	3.6786E-05	0.49	0.713
RB * NTL * K	4.1644E-04	0.431	3.45	1.2073E-04	1.97	0.132
RB * SPR * SDR	1.5766E-04	0.523	4.19	3.7647E-05	0.85	0.509
RB * SPR * CV	1.4690E-04	0.551	2.21	6.6617E-05	0.71	0.517
RB * SPR * K	1.1965E-04	0.717	2.87	4.1693E-05	2.39	0.094 †
RB * SDR * CV	6.3984E-05	0.716	2.86	2.2347E-05	0.41	0.738
RB * SDR * K	1.4350E-04	0.435	1.74	8.2445E-05	1.15	0.334
RB * CV * K	5.5902E-05	0.944	1.89	2.9615E-05	1.27	0.304
NTL * SPR * SDR	1.8924E-02	0.319	5.11	3.7060E-03	3.98	0.004 **
NTL * SPR * CV	8.5138E-03	0.381	3.05	2.7925E-03	5.18	0.006 **
NTL * SPR * K	4.2259E-02	0.492	3.93	1.0745E-02	16.75	0.000 ***
NTL * SDR * CV	6.4532E-03	0.400	3.20	2.0176E-03	3.15	0.038 *
NTL * SDR * K	3.1807E-01	0.257	2.05	1.5482E-01	40.71	0.000 ***
NTL * CV * K	1.0956E-02	0.651	2.60	4.2089E-03	12.10	0.000 ***
SPR * SDR * CV	1.2330E-01	0.810	3.24	3.8064E-02	29.49	0.000 ***
SPR * SDR * K	9.4335E-02	0.516	2.07	4.5672E-02	0.68	0.521
SPR * CV * K	2.2261E-01	0.705	1.41	1.5789E-01	32.59	0.000 ***
SDR * CV * K	3.3739E-01	0.850	1.70	1.9841E-01	30.19	0.000 ***

***, **, *, and † indicate significance at α=.001, .01, .05, and .10, respectively

Figure 29. Proportion Tardy (PT): Repeated Measures ANOVA Tests of Within-Subjects Effects

Source	Type III Sum of Squares	Greenhouse-Geisser Estimate of Epsilon	Corrected df	Mean Square	F	Significance
TM	7.1480E+08	0.293	1.17	6.1038E+08	564.56	0.000 ***
RB	2.1889E+07	0.616	1.23	1.7765E+07	323.89	0.000 ***
NTL	2.3192E+11	0.252	1.01	2.3044E+11	986.55	0.000 ***
SPR	1.0395E+12	0.511	1.02	1.0174E+12	2519.25	0.000 ***
SDR	1.2375E+10	0.561	1.12	1.1034E+10	687.79	0.000 ***
CV	1.1267E+09	1.000	1.00	1.1267E+09	180.54	0.000 ***
K	2.8881E+06	1.000	1.00	2.8881E+06	3.92	0.079 †
TM * RB	2.1129E+05	0.583	4.67	4.5280E+04	1.09	0.378
TM * NTL	1.3314E+09	0.093	1.49	8.9165E+08	472.14	0.000 ***
TM * SPR	1.0139E+09	0.169	1.35	7.5130E+08	808.89	0.000 ***
TM * SDR	5.4039E+06	0.422	3.37	1.6013E+06	9.76	0.000 ***
TM * CV	2.2596E+07	0.609	2.44	9.2772E+06	91.26	0.000 ***
TM * K	4.8797E+05	0.445	1.78	2.7394E+05	10.50	0.002 **
RB * NTL	2.8890E+06	0.383	3.07	9.4208E+05	10.86	0.000 ***
RB * SPR	3.1860E+07	0.379	1.52	2.1024E+07	301.48	0.000 ***
RB * SDR	2.8948E+05	0.622	2.49	1.1627E+05	1.97	0.155
RB * CV	3.8298E+05	0.825	1.65	2.3205E+05	4.61	0.033 *
RB * K	2.8051E+03	0.923	1.85	1.5198E+03	0.69	0.505
NTL * SPR	2.9575E+11	0.126	1.01	2.9236E+11	932.06	0.000 ***
NTL * SDR	1.7612E+09	0.272	2.17	8.1075E+08	522.75	0.000 ***
NTL * CV	5.6548E+09	0.267	1.07	5.2918E+09	439.01	0.000 ***
NTL * K	8.0225E+05	0.392	1.57	5.1165E+05	4.07	0.048 *
SPR * SDR	6.7343E+09	0.418	1.67	4.0229E+09	661.73	0.000 ***
SPR * CV	2.9206E+08	0.579	1.16	2.5202E+08	47.84	0.000 ***
SPR * K	3.5185E+05	0.641	1.28	2.7462E+05	0.77	0.429
SDR * CV	6.9512E+07	0.811	1.62	4.2845E+07	62.82	0.000 ***
SDR * K	5.7763E+06	0.500	1.00	5.7763E+06	3.92	0.079 †
CV * K	1.1735E+04	1.000	1.00	1.1735E+04	0.04	0.838
TM * RB * NTL	7.3663E+05	0.189	6.04	1.2196E+05	1.02	0.425
TM * RB * SPR	5.8021E+05	0.320	5.13	1.1318E+05	1.77	0.137
TM * RB * SDR	8.1329E+05	0.327	5.23	1.5564E+05	2.25	0.062 †
TM * RB * CV	2.5092E+05	0.555	4.44	5.6553E+04	0.88	0.491
TM * RB * K	2.1813E+04	0.459	3.67	5.9434E+03	1.87	0.145
TM * NTL * SPR	1.9848E+09	0.062	1.97	1.0066E+09	538.82	0.000 ***
TM * NTL * SDR	7.8065E+06	0.144	4.61	1.6921E+06	4.60	0.002 **
TM * NTL * CV	5.9193E+07	0.192	3.07	1.9278E+07	66.70	0.000 ***
TM * NTL * K	7.0335E+05	0.162	2.59	2.7201E+05	4.80	0.012 *
TM * SPR * SDR	3.6707E+06	0.262	4.19	8.7703E+05	4.10	0.007 **
TM * SPR * CV	2.2793E+07	0.376	3.01	7.5757E+06	59.26	0.000 ***
TM * SPR * K	5.1565E+05	0.263	2.11	2.4470E+05	6.05	0.009 **
TM * SDR * CV	5.8132E+05	0.537	4.30	1.3524E+05	1.17	0.338
TM * SDR * K	9.7594E+05	0.223	1.78	5.4788E+05	10.50	0.002 **
TM * CV * K	4.5552E+04	0.461	1.84	2.4696E+04	0.85	0.438
RB * NTL * SPR	9.0084E+06	0.221	3.53	2.5485E+06	20.32	0.000 ***
RB * NTL * SDR	4.9145E+05	0.260	4.16	1.1820E+05	0.97	0.436
RB * NTL * CV	1.3490E+06	0.408	3.27	4.1281E+05	8.30	0.000 ***
RB * NTL * K	8.6651E+03	0.496	3.96	2.1854E+03	0.66	0.625
RB * SPR * SDR	6.5318E+05	0.330	2.64	2.4722E+05	2.35	0.104
RB * SPR * CV	3.9703E+05	0.435	1.74	2.2808E+05	3.27	0.071 †
RB * SPR * K	5.5200E+03	0.565	2.26	2.4422E+03	0.76	0.494
RB * SDR * CV	2.9997E+05	0.688	2.75	1.0893E+05	3.57	0.031 *
RB * SDR * K	5.6101E+03	0.461	1.85	3.0396E+03	0.69	0.505
RB * CV * K	7.3145E+03	0.964	1.93	3.7930E+03	1.07	0.364
NTL * SPR * SDR	1.7617E+09	0.164	2.62	6.7189E+08	378.03	0.000 ***
NTL * SPR * CV	6.5406E+09	0.146	1.17	5.5952E+09	381.13	0.000 ***
NTL * SPR * K	5.8351E+05	0.178	1.42	4.0990E+05	1.68	0.224
NTL * SDR * CV	2.1271E+07	0.334	2.68	7.9507E+06	18.89	0.000 ***
NTL * SDR * K	1.6045E+06	0.196	1.57	1.0233E+06	4.07	0.048 *
NTL * CV * K	4.6232E+03	0.337	1.35	3.4309E+03	0.02	0.936
SPR * SDR * CV	4.9518E+07	0.481	1.92	2.5755E+07	23.11	0.000 ***
SPR * SDR * K	7.0371E+05	0.320	1.28	5.4924E+05	0.77	0.429
SPR * CV * K	2.2905E+04	0.529	1.06	2.1642E+04	0.06	0.829
SDR * CV * K	2.3470E+04	0.500	1.00	2.3470E+04	0.04	0.838

***, **, *, and † indicate significance at α=.001, .01, .05, and .10, respectively

Figure 30. Material Movements (MM): Repeated Measures ANOVA Tests of Within-Subjects Effects

As Figure 28 - Figure 30 indicate, the sample size and methods applied were ideal in that they allow a mix of statistically significant and non-significant effects to be identified (it is well known that any measure can be made statistically significant if the sample size is increased sufficiently, so too large of a sample can be a problem if all effects are shown to be statistically significant). As a way to further identify interesting conditions, plots of mean values for the different effects were examined. In some instances, a statistically significant effect was apparently calculated primarily because of the power associated with the experimental design. The eminent statistical researcher Jacob Cohen (1994) is just one of many scholars who has advocated not being overly focused on statistical significance measures associated with null hypothesis testing. Kirk (1995) said that practical significance means that the difference in means is “large enough to be useful in the real world”, as opposed to statistical significance, which often only provides insights of “trivial scientific interest” (Cohen et al., 2003) and “does not guarantee that something important, or even meaningful, has been found” (Hays, 1994). Bragg, Duplaga, and Penlesky (2005) observed, “As can be the case with any simulation study, statistically significant results may not be of practical significance.” Rather than overwhelm the reader with discussion of *every* statistically significant effect, this chapter will focus on those that are judged to *also* have practical (i.e., managerial) significance. Since practical significance is inherently subjective, the percent difference in the dependent variable between treatment conditions, along with a graph, is usually provided so that readers can make their own evaluations.

As is common with the analysis of complex experimental designs, statistics were not calculated for four-way and higher order interactions due to the difficulty in interpreting the results. As noted by Keppel (1991), care must be taken to analyze an effect when related higher order effects are statistically significant. In many instances, the higher order (2- and 3-way interaction) effects will be both practically and statistically significant, and thus will be discussed instead of the main effect (for a single factor), even if the main effect is statistically significant. In other cases, higher order effects are statistically significant but not practically significant (e.g., the differences in the dependent variable are under one percent), and the lower order effects will be discussed to avoid unnecessary complexity.

5.1 Hypothesis 1: The forms of bar coding with stochastic read times should show worse mean flow time (MFT) and proportion tardy (PT) performance than their deterministic bar coding counterparts. Stated more formally, TM4 should have numerically higher MFT and PT than TM2, and TM5 should have numerically higher MFT and PT than TM3, statistically significant at no more than $p<.10$ when performing pairwise comparisons.

The ANOVAs in Figure 28 and Figure 29 indicate differences in MFT and PT between the TM levels, and they also indicate a TM*NTL interaction, as illustrated in Figure 31 and Figure 32. Contrary to hypothesis 1, though, pairwise tests showed that the differences between the deterministic and stochastic levels of fast and slow bar coding (TM2 versus TM4, and TM3 versus TM5) were not statistically significant at $p<.10$.

Furthermore, Figure 31 and Figure 32 illustrate that the largest difference between TM2 versus TM4 and TM3 versus TM5 at any of the NTL levels is less than .1 percent for MFT, and less than .25 percent for PT. The differences between the solid and hollow shapes (between the deterministic and stochastic forms of bar coding) are virtually indistinguishable (you cannot even see the hollow symbols in the graph, because the solid shapes are on top of them). In contrast, the differences between RFID (TM1) versus fast bar coding (TM2 or TM4) versus slow bar coding (TM3 or TM5) are both statistically and practically significant, as will be discussed in the analysis for later hypotheses, along with the TM*NTL interaction that leads to the curves of varying shapes seen in Figure 31 and Figure 32.

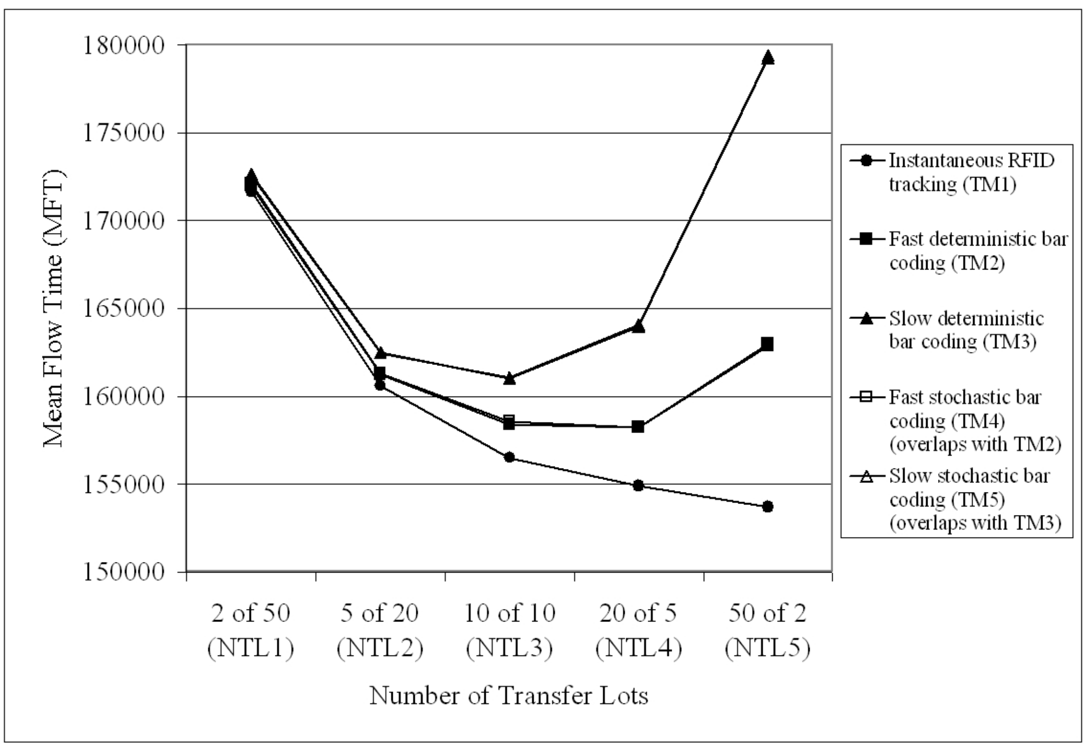


Figure 31. Mean Flow Time (MFT) for Transfer Lot Tracking Mechanism (TM1-TM5) and Number of Transfer Lots (NTL)

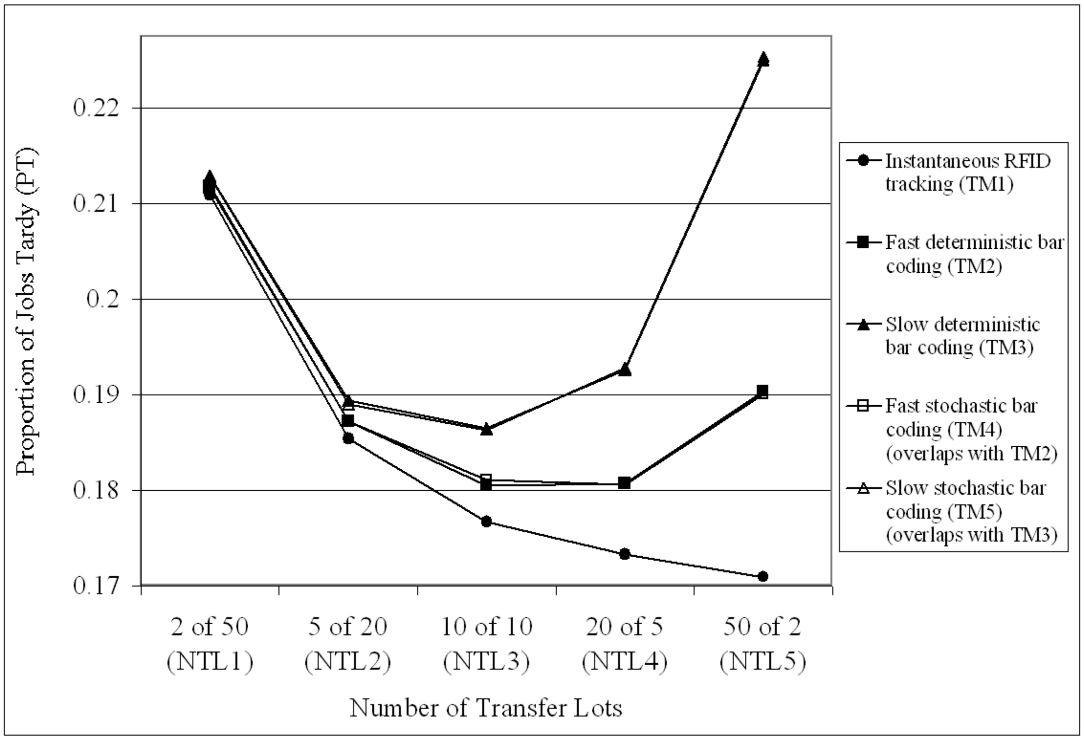


Figure 32. Proportion Tardy (PT) for Transfer Lot Tracking Mechanism (TM1 to TM5) and Number of Transfer Lots (NTL)

The lack of significance between the deterministic and stochastic forms of bar coding (TM2 versus TM4, and TM3 versus TM5) has several plausible causes. The stochastic TM levels (TM4 and TM5) represented situations where it would potentially take a long time to correctly scan a transfer lot, which might disrupt material flow and cause a downstream work center to switch to a different job type, thus wasting capacity when switching between job types. When there is a low setup/processing time (SPR) ratio (e.g., SPR1), the penalty for switching between job types is relatively non-severe, and so there is relatively little penalty even if a particularly long upstream scan unnecessarily causes extra setups downstream due to the delay in the upstream transfer lot being moved. When the SPR ratio is high (e.g., SPR3), there is a good chance that even if the movement of an upstream transfer lot is delayed to a particularly long scan time, the downstream work center will be busy performing a setup on the leading transfer lot for that job type, and will not finish processing that downstream lot until the upstream lot has finally been read and is ready to be moved.

Researchers must balance the desire for realism (by including every possible factor) in models versus parsimony (to avoid overwhelming computing and cognitive power to compute and analyze the results). The key takeaway is that stochastic read times are unlikely to lead to significantly different results compared to deterministic read times for similar models. This should allow future researchers to focus on other factors that are necessary to realistically differentiate between the conditions that make RFID ideal or not compared to data collection alternatives such as bar coding. To prevent unnecessary complexity in the subsequent analyses in this dissertation, attention will be focused on RFID (TM1) and the deterministic forms of bar coding (TM2 and TM3).

The **key findings for Hypothesis 1** can be summarized as follows:

Statistical tests revealed that the performance differences for mean flow time (MFT) and proportion of jobs tardy (PT) between the deterministic and stochastic levels of fast and slow bar coding (TM2 versus TM4, and TM3 versus TM5) were not statistically significant at $p<.10$. Thus, as seen in Figure 31 and Figure 32, stochastic bar coding read times (TM4 and TM5) are unlikely to lead to significantly different results compared to deterministic read times (TM2 and TM3). *Because these results indicate there is no difference in mean flow time and proportion tardy based on the use of deterministic versus stochastic bar* *coding read times, future research can use deterministic times and therefore use more parsimonious models or have additional space in the experimental design to incorporate additional factors that lead to more realistic modeling of RFID, bar coding, and the manufacturing process.*

5.2 Hypothesis 2: With increased transfer lots (NTL), mean flow time (MFT) and proportion of jobs tardy (PT) will improve when using RFID (with TM1). Stated more formally, with the tracking mechanism held constant at level TM1, increasing NTL should result in increasingly smaller MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. When *not* using RFID (when not using TM1), increased NTL will result in better MFT and PT performance at first, and then lead to worse performance. Stated more formally, when using TM2 - TM5, increasing NTL should result in increasingly smaller MFT and PT up to some switchover point, before further increasing NTL results in increasingly larger MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels.

The ANOVAs in Figure 28 and Figure 29 suggest that there is a TM*NTL interaction for MFT and PT, $p<.001$. Figure 31 and Figure 32 show plots of the means and visually support Hypothesis 2. Post-hoc tests (pairwise comparisons) indicate statistically significant differences ($p<.01$) in MFT and PT performance between adjacent NTL levels when holding the tracking mechanism (TM) constant, and thus also support Hypothesis 2.

Figure 31 and Figure 32 show that MFT and PT performance get better with increased lot streaming when RFID (TM1) is used, but with diminishing returns (the curve becomes increasingly flat with increased NTL). The RFID scenario in Figure 31 and Figure 32 allows the benefits of increased lot streaming to be seen without any trade-off from tracking the transfer lots. Figure 31 and Figure 32 show that by splitting the original job size into ever smaller transfer lots, the smaller transfer lots can independently move through the system and better utilize capacity that goes wasted when work centers have to wait for larger lot sizes to move through the system. Better capacity utilization allows better MFT and PT performance.

Given that the incremental benefits of lot streaming grow smaller with increasing NTL, it makes sense that when RFID (TM1) is *not* used, though, the overall (net) MFT and PT performance would result in the U-shaped curves for bar coding (TM2 – TM5) seen in Figure 31 and Figure 32. As the discussion of Hypothesis 2 in Chapter 3 predicted, the time spent performing the bar code tracking activity for an increasing number of transfer lots eventually offset the performance gains from using the increased lot streaming (higher NTL), and thus we see the U-shaped curves in Figure 31 and Figure 32 for the bar coding models (TM2 - TM5). Although increased lot streaming results in better flow, those gains are eventually offset by the time "wasted" by the bar code tracking process when there are many transfer lots.

None of the previous literature on lot streaming modeled the effect of the time spent tracking the transfer lots (the TM factor). This research gives some perspective on the point at which performance gets worse with increased lot streaming when using tracking mechanisms such as bar coding that require time to position and scan the transfer lots. Figure 31 and Figure 32 show that with slow bar coding (TM3 or TM5), performance for MFT and PT gets worse after an intermediate level of lot streaming (e.g., the NTL3 level of 10 transfer lots when the original job size is 100 units). Compared to slow bar coding, fast bar coding (TM2 or TM4) is able to benefit slightly more from increased lot streaming before returns from increased NTL become negative, because fast bar coding pays less of a time penalty for each additional transfer lot that must be tracked. MFT performance improves with increased lot streaming when moving from NTL3 to NTL4, but PT performance worsens when moving from NTL3 to NTL4.

Interestingly, the power from the experimental design makes the difference between RFID (TM1) versus fast (TM2 or TM4) and slow (TM3 or TM5) bar coding statistically significant for MFT ($p<.05$ and $p<.001$, respectively) and PT ($p<.10$ and $p<.001$, respectively), even when there are only 2 transfer lots of 50 units each (NTL1). When there are only 2 transfer lots of 50 units each (NTL1), the largest reduction in MFT when using RFID (TM1) instead of one of the bar coding factors (TM2-TM5) is less than .6 percent, and the largest PT reduction between RFID (TM1) and any of the bar coding factors (TM2-TM5) is less than 1 percent. Such small percent differences may not be practically significant enough to motivate investment in RFID for many companies, especially if they are already using bar coding and they are not planning to use RFID to enable the effective tracking of jobs split into greater numbers of transfer lots. With more lot streaming (higher NTL levels), the differences between RFID and fast and slow bar coding become more statistically significant ($p<.001$ for all MFT and PT comparisons).

Visual examination of the data in Figure 31 and Figure 32 shows that the largest differences in MFT and PT performance for the different types of tracking mechanisms are when comparing RFID, fast bar coding, and slow bar coding against each other at moderate (e.g., NTL3) and higher levels of lot streaming. For example, RFID (TM1) results in a MFT reduction of 2.8 percent compared to slow deterministic bar coding (TM3) at NTL3, and a PT reduction of 5.3 percent. When comparing RFID (TM1) at NTL5 (where TM1 has its best performance) versus slow deterministic bar coding (TM3) at NTL3 (where TM3 has its best performance), the reduction in MFT is 4.6 percent, and the reduction in PT is 8.3 percent.

The **key findings related to the analysis for Hypothesis 2** can be summarized as follows:

1. When there are only 2 transfer lots of 50 units each (NTL1), the difference between RFID (TM1) versus fast (TM2 or TM4) and slow (TM3 or TM5) bar coding is statistically significant for mean flow time ($p<.05$ and $p<.001$, respectively) and proportion tardy ($p<.10$ and $p<.001$, respectively). Using only 2 transfer lots of 50 units each (NTL1) represents a situation where the capabilities of RFID to enhance processes are not fully utilized. For example, RFID enables higher levels of lot streaming (higher NTL) than were previously possible, because it allows material to be automatically tracked without constraints due to labor, traceability, and process conformance that are present even when other technologies such as bar coding are used. For 2 transfer lots of 50 units each (NTL1), even though there was statistical significance, there was little practical difference (less than 1 percent) in mean flow

time (MFT) and proportion tardy (PT) performance between RFID and bar coding (see Figure 31 and Figure 32). *Given the higher cost of RFID, it may make more sense to use bar coding if the process is not enhanced (e.g., if increased lot streaming is not used) to take advantage of RFID's key enabling features such as better traceability. Stated another way, RFID requires process changes to be substantially beneficial (e.g., using RFID to reduce flow times and proportion tardy by more than a single percent compared to bar coding requires increased lot streaming, as represented by NTL3 – NTL5).*

2. There were statistically significant differences ($p<.01$) in mean flow time (MFT) and proportion tardy (PT) between adjacent lot streaming (NTL) levels when holding the tracking mechanism (TM) constant. The time spent performing the bar code tracking activity (TM2-TM5) eventually outweighs the performance gains from increasing the number of transfer lots (NTL), and thus generates U-shaped curves in Figure 31 and Figure 32 for the fast (TM2 and TM4) and slow (TM3 and TM5) bar coding tracking activities. Previous research had not considered the time necessary to track transfer lots, and thus had suggested that increased lot streaming (higher NTL) always resulted in monotonically increasing performance. Because of the need to compare RFID (TM1) against existing data collection alternatives, this result is important regardless of whether RFID or bar coding (TM2-TM5) is being modeled. *This research shows the importance of incorporating attributes of the data collection method (e.g., RFID or fast or slow bar coding as represented by the TM factor levels) in models in order to develop accurate conclusions about processes.*

3. When using 5 transfer lots or more (NTL2-NTL5), the differences between RFID (TM1) and fast (TM2 and TM4) and slow (TM3 and TM5) bar coding become more statistically significant ($p<.001$ for all MFT and PT comparisons between NTL2 and NTL5, as opposed to some comparisons that were only $p<.10$ or $p<.05$ for NTL1). The rise in statistically significant differences between RFID (TM1) and bar coding (TM2-TM5) with increased lot streaming (higher NTL) parallels an increase in practically significant differences, allowing improvement of over 5 percent when RFID is used, as seen Figure 31 and Figure 32. As noted earlier, the better traceability of RFID enables higher levels of lot streaming (as represented by NTL3 – NTL5); this leads RFID to exhibit substantially better MFT and PT performance than the bar code alternatives (TM2 – TM5). *These results show that if RFID is used to enable substantially changed processes (e.g., because its better traceability facilitates increased lot streaming as represented by NTL3 – NTL5), it can lead to much better performance (e.g., mean flow time and proportion tardy) than bar coding.*
4. As noted earlier, the improvement in mean flow time (MFT) and proportion tardy (PT) performance between each of the adjacent lot streaming (NTL) levels is statistically significant at $p<.001$ when RFID (TM1) is used. From a practical perspective, though, the percent reduction in mean flow time (MFT) when moving from 20 transfer lots of size 5 (NTL4) to 50 transfer lots of size 2 (NTL5) is only .8 percent, and the reduction in proportion tardy (PT) is only 1.4 percent. In contrast, the reduction in MFT when moving from 2 transfer lots of size 50 (NTL1) to 5 transfer lots of size 20 (NTL2) is 2.6 percent, and the reduction in PT is 12.1 percent.

As can be seen in Figure 31 and Figure 32, there are diminishing returns in MFT and PT performance improvements with increased use of lot streaming (higher NTL) when RFID is used. *Even though RFID can enable valuable process changes for manufacturers (e.g., increased use of lot streaming as a result of better traceability compared to bar coding), those process changes may offer diminishing returns (e.g., ever smaller reductions in mean flow time and proportion tardy) when carried to extremes (e.g., splitting a job of 100 units into 50 transfer lots, as represented by NTL5).*

5.3 Hypothesis 3: The improvement in mean flow time (MFT) and proportion of jobs tardy (PT) performance with increased lot streaming (higher NTL) should be lower when the setup / processing time ratio increases (when SPR increases). Stated more formally, an NTL*SPR interaction effect (statistically significant at no more than $p<.10$) is expected to be identified for MFT and PT.

The ANOVAs in Figure 28 and Figure 29 suggest an NTL*SPR interaction effect ($p<.05$ for MFT, $p<.001$ for PT). Because the earlier analysis demonstrated that performance gets better before getting worse when non-instantaneous tracking is used (when not using TM1), plots and analysis for this hypothesis were used with the tracking method level fixed on RFID (TM1). As noted in Hypothesis 2 and throughout this dissertation, RFID enables an increase in lot streaming (higher NTL) than was previously practically possible. A close examination of Figure 33 and Figure 34 in conjunction with the ANOVAs provides support for Hypothesis 3, that the MFT and PT performance benefits with RFID-enabled increases in lot streaming vary at different SPR levels. For example, when SPR1 is used, moving from NTL1 to NTL2 results in improvement of 8.97 percent for MFT, but when SPR2 is used, the improvement is only 6.48 percent, and when SPR3 is used, the improvement is only 5.12 percent. When moving from NTL1 to NTL5, the MFT gains are 14.69 percent, 10.41 percent, and 8.35 percent, for each of the respective SPR levels. Similarly, when SPR1 is used, moving from NTL1 to NTL2 results in improvement of 15.27 percent for PT, but when SPR2 is used, the improvement is only 11.79 percent, and when SPR3 is used, the improvement is only 9.57 percent. When moving from NTL1 to NTL5, the PT gains are 23.69 percent, 18.18 percent, and 15.49 percent, for each of the respective SPR levels.

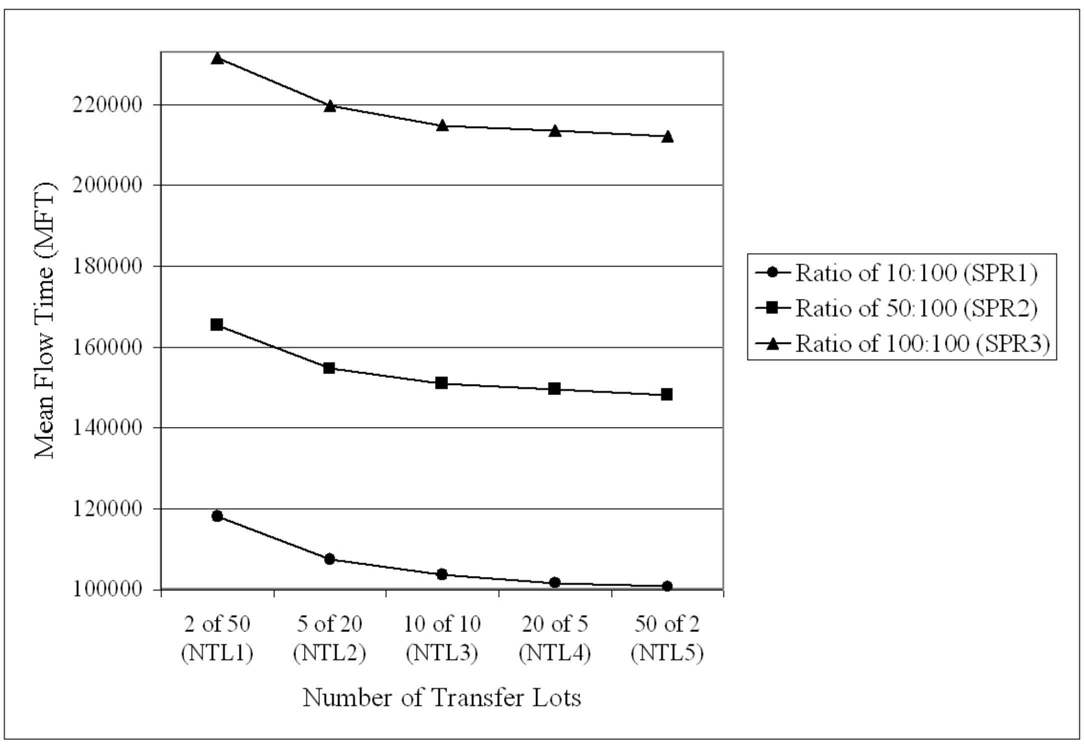


Figure 33. When Higher Setup/Processing Time Ratio (SPR), Smaller Percentage Improvement in Mean Flow Time (MFT) With RFID-Enabled (TM1) Increase in Number of Transfer Lots (NTL)

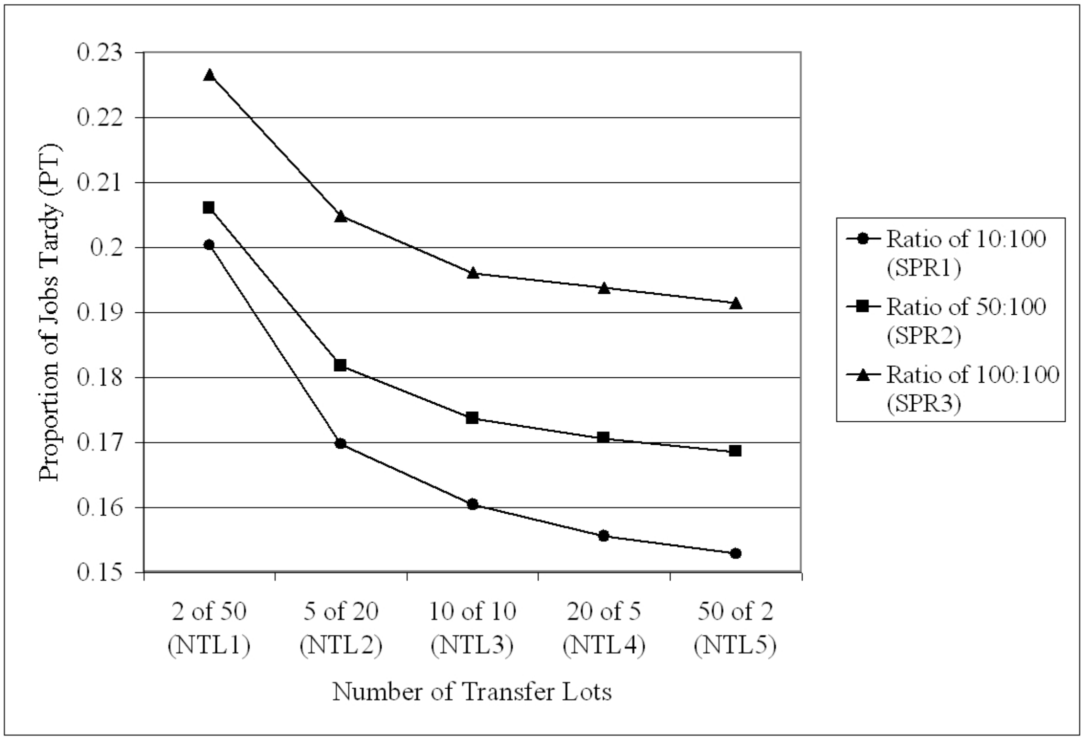


Figure 34. When Higher Setup/Processing Time Ratio (SPR), Smaller Improvement in Proportion of Jobs Tardy (PT) With RFID-Enabled (TM1) Increase in Number of Transfer Lots (NTL)

This analysis shows that when examining the results only from the perspective of gains in mean flow time (MFT) and proportion of jobs tardy (PT), companies might be particularly inclined to use increased lot streaming (i.e., higher NTL) enabled by RFID when there are low setup/processing time ratios (e.g., SPR1), because the improvement is greater compared to when the SPR ratio is higher. As will be discussed for Hypothesis 4, though, the trade-off in material movements with low setup/processing time ratios should also be considered.

The **key findings related to the analysis for Hypothesis 3** can be summarized as follows:

There is an interaction effect between the number of transfer lots used (NTL) and the setup/processing time ratio (SPR), statistically significant at $p<.05$ for mean flow time (MFT), and at $p<.001$ for proportion tardy (PT). As can be seen in Figure 33 and Figure 34, the percent reductions in MFT and PT are greatest when the setup/processing time ratio is low (e.g., the 10:100 ratio of SPR1). *The use of smaller lot sizes enabled by RFID drives reductions in mean flow time and proportion tardy, and those reductions are sensitive to the operating conditions (e.g., the setup/processing time ratio).*

5.4 Hypothesis 4: With the tracking mechanism held constant at RFID (TM1), increasing the amount of lot streaming (NTL) should result in increasingly numerous material movements (MM), statistically significant at no more than $p < .10$ when performing pairwise comparisons between adjacent NTL levels.

Post-hoc tests motivated by the ANOVA in Figure 30 indicate statistically significant increases ($p<.001$) in material movements (MM) between adjacent lot streaming (NTL) levels when using instantaneous RFID tracking (TM1). The plot in Figure 35 provides visual support of the magnitude of the increase in material movements, also supporting Hypothesis 4.

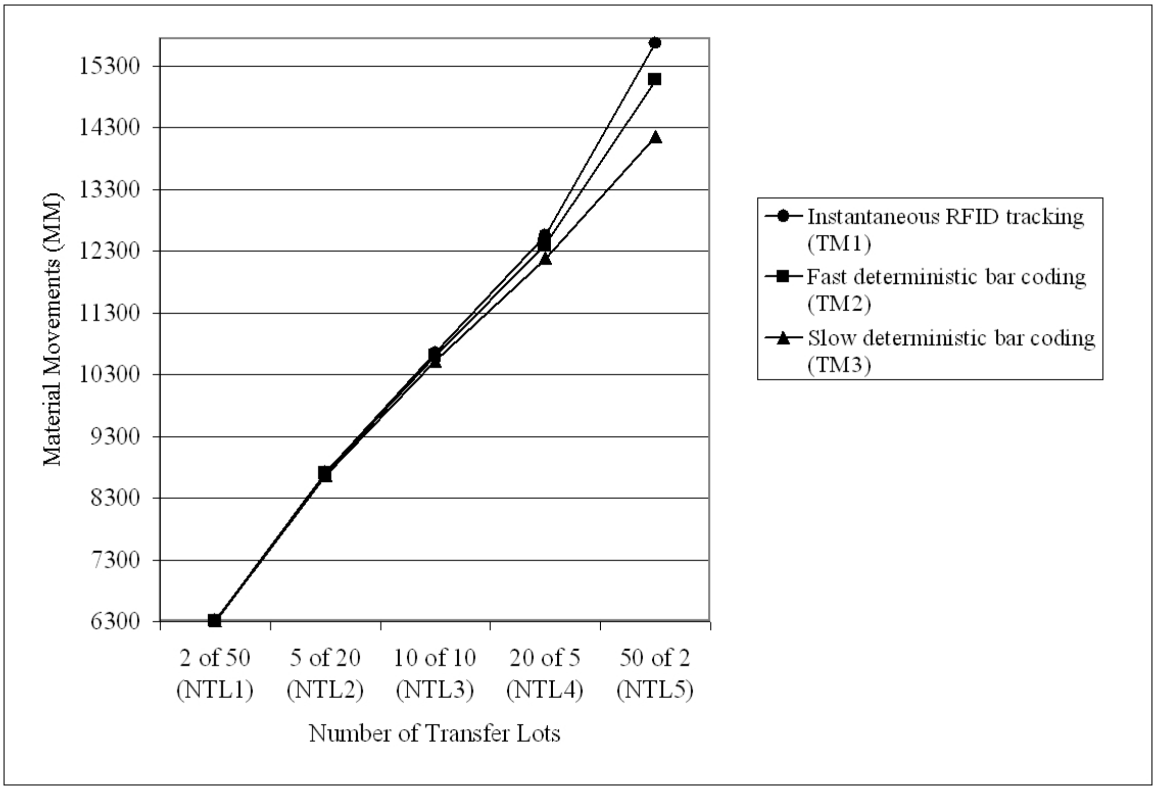


Figure 35. Material Movements (MM) for Transfer Lot Tracking Mechanism (TM) and Number of Transfer Lots (NTL)

Figure 31 and Figure 32 indicated that an increased number of transfer lots lead to reductions in mean flow time (MFT) and proportion tardy (PT), whereas Figure 35 showed that the number of material movements (MM) increase with increased lot streaming (higher NTL). In other words, MFT and PT performance improves with increased lot streaming, but MM performance simultaneously gets worse. Because each of the performance measures is illustrated in a different figure, it may not be clear how the rates of change for each variable are related. Figure 36 shows this more clearly for the RFID tracking mechanism (TM1). Note that the left vertical axis is for the *decrease* in MFT and PT from a baseline of 2 transfer lots of 50 units (NTL1), and the right vertical axis is for an *increase* in MM from a baseline of 2 transfer lots of 50 units

(NTL2). Because the data points in Figure 36 show the percent change in MFT, PT, and MM when increasing the number of transfer lots away from the NTL1 baseline, the horizontal axis only shows four positions even though there are five NTL factor levels.

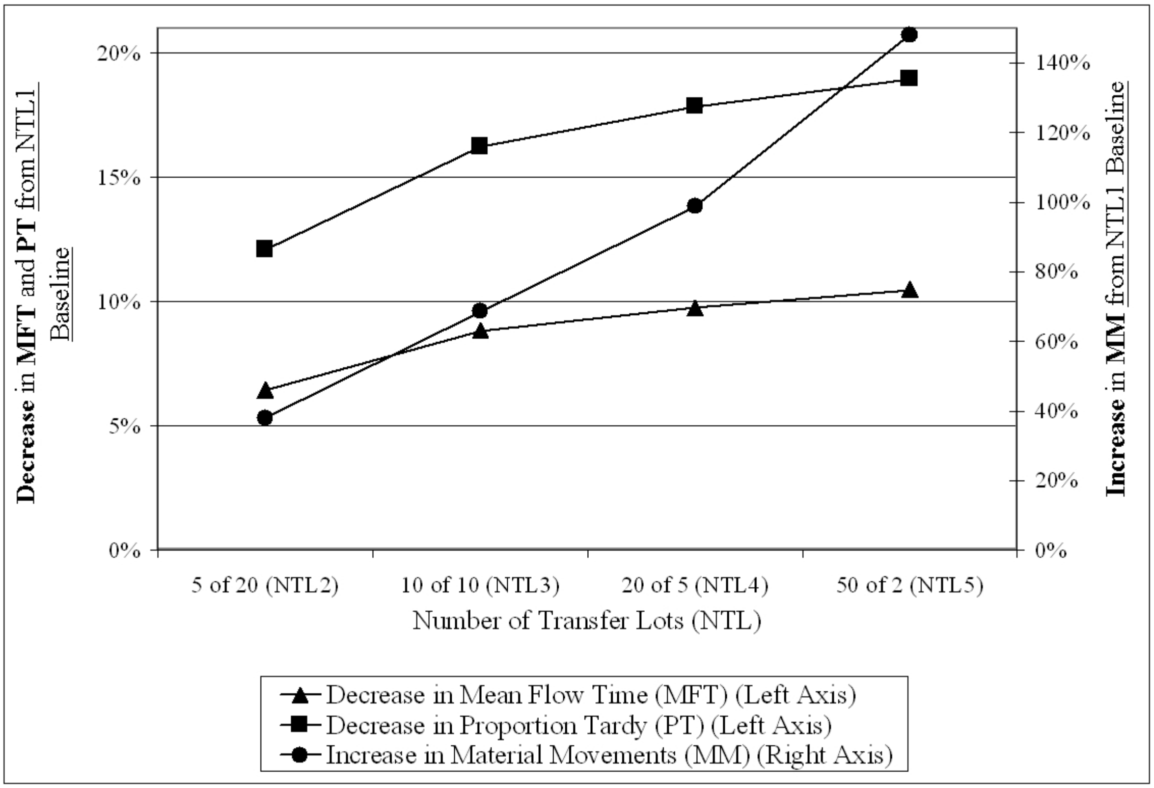


Figure 36. Trade-Off Between Mean Flow Time (MFT) and Proportion of Jobs Tardy (PT) Versus Material Movements (MM) with Increased Number of Transfer Lots (NTL) When Using RFID (TM1)

The **key findings related to Hypothesis 4** can be summarized as follows:

Post-hoc tests motivated by the ANOVA in Figure 30 indicate statistically significant increases ($p<.001$) in the total number of material movements (MM) between adjacent lot streaming (NTL) levels when using RFID (TM1). The plot in Figure 35 provides visual support of the magnitude of the increase in material movements (over 140 percent), also supporting Hypothesis 4. Figure 36 shows that the diminishing returns in mean flow time (MFT) and proportion of jobs tardy (PT) improvement from increased lot streaming (higher NTL) must be traded-off against the relatively sharper increase in material movements (MM). *As with other technology investments and process changes, RFID and the move to incorporate reduced lot sizes (higher NTL) sometimes involve trade-offs (e.g., reduced flow times and proportion tardy are obtained at the expense of increased material movements between work centers).*

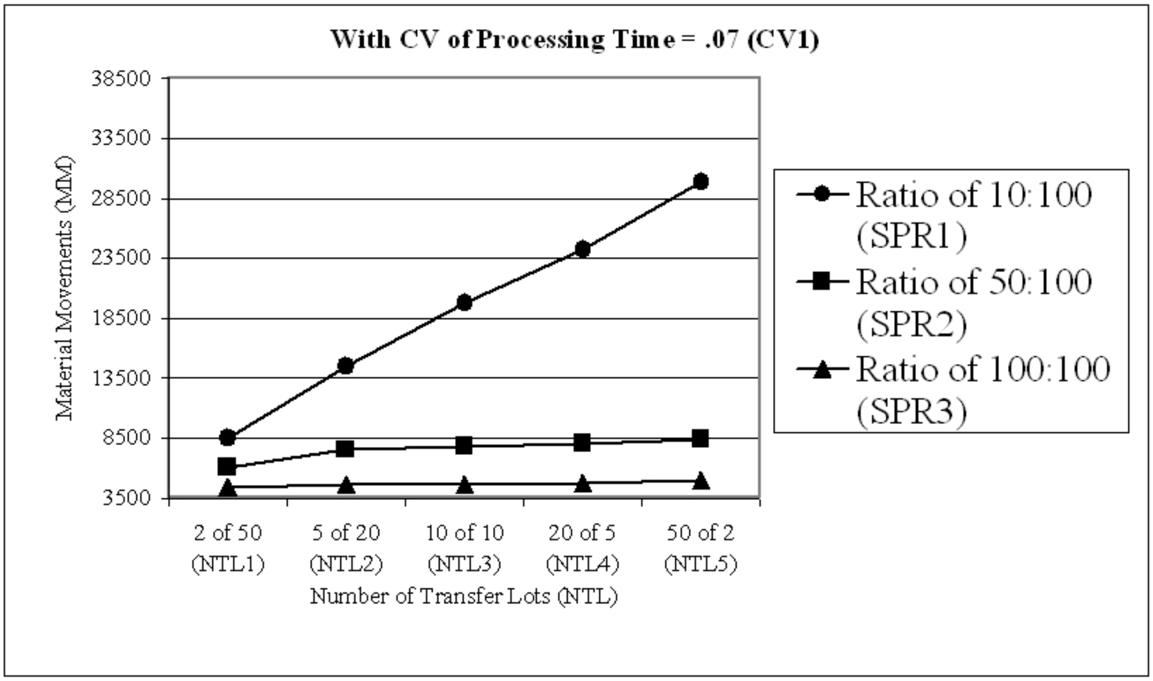
5.4.1 Follow-up analysis to Hypothesis 4 to identify operating conditions (e.g., setup/processing time ratios and CV of processing times) where the increase in material movements with more lot streaming is not so severe

Figure 36 shows that when aggregating across the various factor levels, increased lot streaming (higher NTL) results in better mean flow time (MFT) and proportion tardy (PT) performance, but there are diminishing returns, and the MFT and PT improvements must be traded-off against the sharp increases in the number of material movements (MM). A key issue is to identify the operating conditions (e.g., setup/processing time ratio and CV of processing times) where the trade-off is not so severe (where the gains in MFT and PT with increased lot streaming can be attained without such a large increase in MM).

The MM ANOVA for the full experimental design (Figure 30) indicates an interaction involving the extent of lot streaming, setup/processing time ratio, and CV of processing time (NTL*SPR*CV), $p<.001$. A follow-up MM ANOVA using just the

RFID (TM1) treatments also indicates a NTL*SPR*CV interaction, $p<.001$. Figure 37 and the following discussion focus on RFID (TM1), because RFID shows improved mean flow time (MFT) and proportion tardy (PT) performance even at the highest levels of lot streaming (NTL), and thus more interesting analysis of the trade-off between MFT and PT versus material movements (MM) is possible. Post-hoc tests indicate that at each combination of NTL and CV, the differences in MM between each of the SPR levels is statistically significant at $p<.001$. Figure 37 shows that the rate of increase in MM with RFID and increased NTL is far greater when the SPR ratio is low (e.g., compare the SPR1 and SPR3 levels). Thus, when the setup time is only a small proportion of the total time needed for a transfer lot at a work center (e.g., SPR1), high usage of transfer lots (e.g., NTL5) may ultimately be inhibited unless material handling is *very* efficient. Furthermore, when there is large CV of processing times (see the plot for CV2 in the bottom half of Figure 37), the increase between NTL4 and NTL5 is particularly dramatic. The difference in MM when comparing CV1 versus CV2 across the same SPR levels at NTL5 is statistically significant at $p<.001$. Like operating conditions with low SPR ratios (e.g., SPR1), operating conditions with high CV (e.g., CV2) may also inhibit RFID use (TM1) with the most extreme forms of lot streaming (e.g., NTL5), unless material handling is very efficient.

\



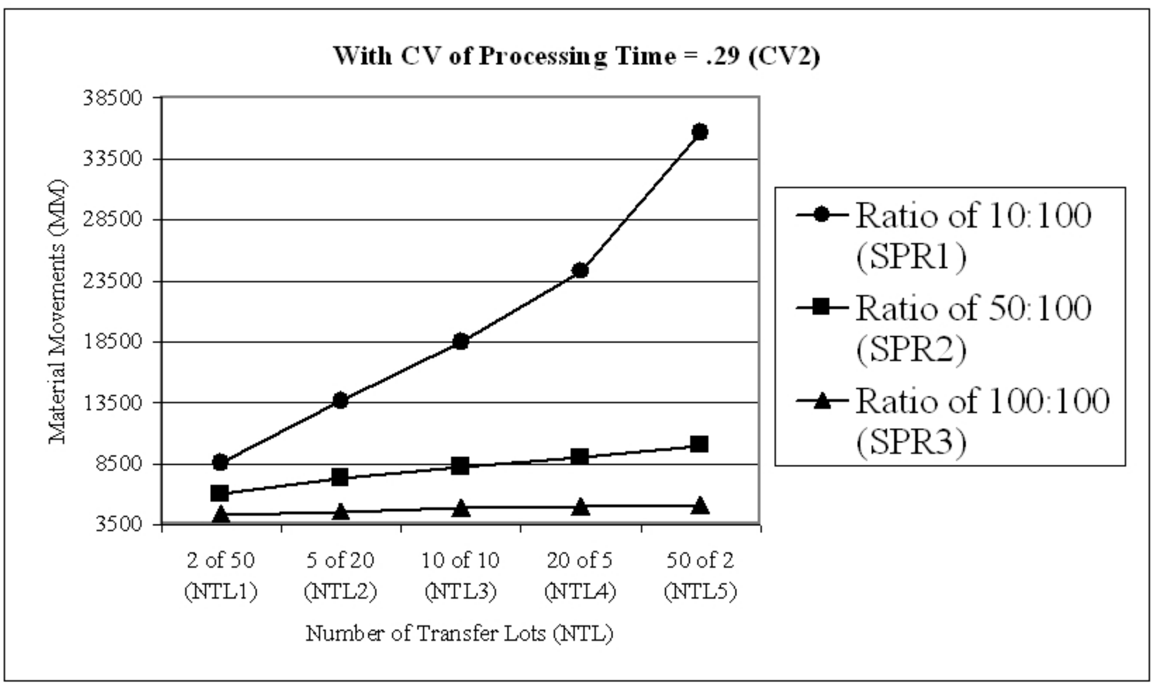


Figure 37. Material Movements (MM) for Number of Transfer Lots (NTL), Setup/Processing Time Ratio (SPR), and CV of Processing Time When Using RFID (TM1)

The reason that medium and high SPR ratios (e.g., SPR2 and SPR3) do not lead to as large of an increase in material movements (MM) when RFID (TM1) is used to enable extreme lot streaming (e.g., NTL5) in Figure 37 might be due to the fact that the leading transfer lot for a job type may arrive at a downstream work center and initiate a relatively long setup. Because of the pull material movement philosophy employed, the trailing transfer lots for that job type at the upstream work center will be processed and accumulate in a queue to be moved while the setup for the leading transfer lot is being performed at the downstream work center. Once the downstream setup has been completed and the leading transfer lot has been processed, several of the upstream transfer lots can then be moved in one movement to the downstream work center. In contrast, with the low SPR ratio (e.g., SPR1), it does not take very long for the leading transfer lot to complete its setup, and so fewer transfer lots accumulate upstream, and thus there are more material movements between work centers in order to keep the downstream work center utilized with the same job type.

The reason that a high CV (e.g., CV2) leads to a relatively large increase in material movements (compare the top and bottom portions of Figure 37), particularly for low SPR ratios (e.g., SPR1), might be due to the fact that when there are large differences in the processing times between operations for a job type, gaps between leading and trailing job types will naturally occur more often. When there is a gap, the dispatching rule logic will look to another (second) job type, possibly at another work center. After the leading transfer lot(s) for that other job type have been processed, the cycle of needing to look for another job type might be repeated (due to a gap in the flow of the second job type). One possible explanation is that this leads to more material movements as the system oscillates between moving material from various job types and upstream work centers due to the gaps in the flow.

The **key findings related to section 5.4.1** can be summarized as follows:

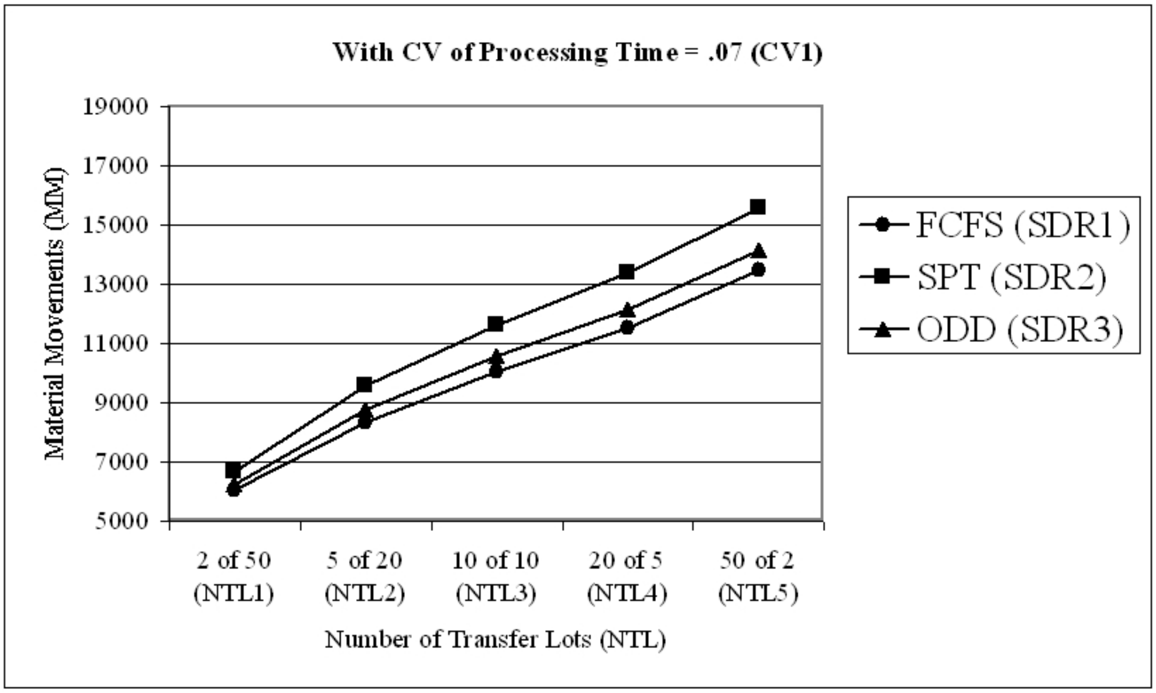
The ANOVA in Figure 30 (as well as a follow-up ANOVA using just the RFID treatments) indicate an interaction between the extent of lot streaming, setup/processing time ratio, and CV of processing time (NTL*SPR*CV) for the number of material movements (MM), $p<.001$. Figure 37 shows that the increase in MM with more lot streaming (higher NTL) is larger when the SPR ratio is lower (e.g., the increase in MM is larger with SPR1 compared to SPR3). Also related to the NTL*SPR*CV interaction, the negative tradeoff of RFID with increased lot streaming will be less when the CV of the processing times between work centers is low (compare the top and bottom portions of Figure 37), so there are advantages in trying to group work centers and material flow to minimize large differences in processing times. When the SPR ratio is low (e.g., SPR1), and especially when the CV of processing times is also large (such as represented by CV2), extreme levels of lot streaming (e.g., NTL5) may not be appropriate, even when automation and RFID is used, because of the massive increase in material movements (e.g., the move from NTL4 to NTL5 results in a 46.7 percent increase under those conditions, statistically significant at $p<.001$). *The increase in the number of material movements associated with RFID and increased lot streaming (higher NTL) is sensitive to the operating conditions (e.g., the setup/processing time ratio and the CV of processing time between work centers). Managers should realize that with moderate and* *high SPR ratios (e.g., SPR2 and SPR3), investments in automated material handling might be necessary when using high levels of lot streaming, regardless of whether RFID is used. When the SPR ratio is low (e.g., SPR1), the increase in material movements with even moderate levels of lot streaming (e.g., NTL2) might be too much even if automated handling is used, thus allowing only minimal levels of lot streaming (e.g., NTL1) to be used.*

5.4.2 Follow-up analysis to Hypothesis 4 to identify operating policies (e.g., secondary dispatching rule) where the increase in material movements might not be so severe

Section 5.4.1 analyzed the operating *conditions* (e.g., setup/processing time ratio and CV of processing times) where the trade-off between the gains in mean flow time (MFT) and proportion tardy (PT) can be attained without such a large increase in material movements (MM) when RFID (TM1) is used to enable increased lot streaming (higher NTL). This section analyzes the operating *policies* (e.g., secondary dispatching rules) that companies can more readily change to minimize the increase in material movements.

Besides the NTL*SPR*CV interaction that was just discussed, the MM ANOVA for the full experimental design (Figure 30) also indicates an interaction involving lot streaming, secondary dispatching rule, and CV of processing time (NTL*SDR*CV), statistically significant at $p<.001$. A follow-up MM ANOVA using just the RFID (TM1) treatments also indicates a NTL*SDR*CV interaction, $p<.001$. Congruent with Figure 37, Figure 38 shows that the growth in material movements between NTL4 and NTL5 is more dramatic when processing times between work centers have a high CV (e.g., CV2).

Post-hoc tests show that the difference in MM when comparing CV1 versus CV2 for each SDR level at NTL5 is statistically significant at p<.001. All of these results support the notion that when RFID is used with extreme amounts of lot streaming (e.g., NTL5) in environments with high CV (e.g., CV2), automated material handling might be practically necessary. Figure 38 shows that at each of the NTL levels, the FCFS rule is best (has the lowest MM value), followed by ODD and SPT, statistically significant at p<.001. Figure 38 also illustrates that the difference between each of the dispatching rules grows between NTL1 and NTL5, statistically significant at p<.001. While there is only a 10.2 percent difference in material movements between the FCFS (SDR1) and SPT (SDR2) dispatching rules at NTL1, the difference grows to 15.5 percent at NTL5. A key takeaway is that from the perspective of material movements (MM), the choice of secondary dispatching rule becomes more critical when RFID (TM1) is used with extensive amounts of lot streaming (e.g., NTL5).



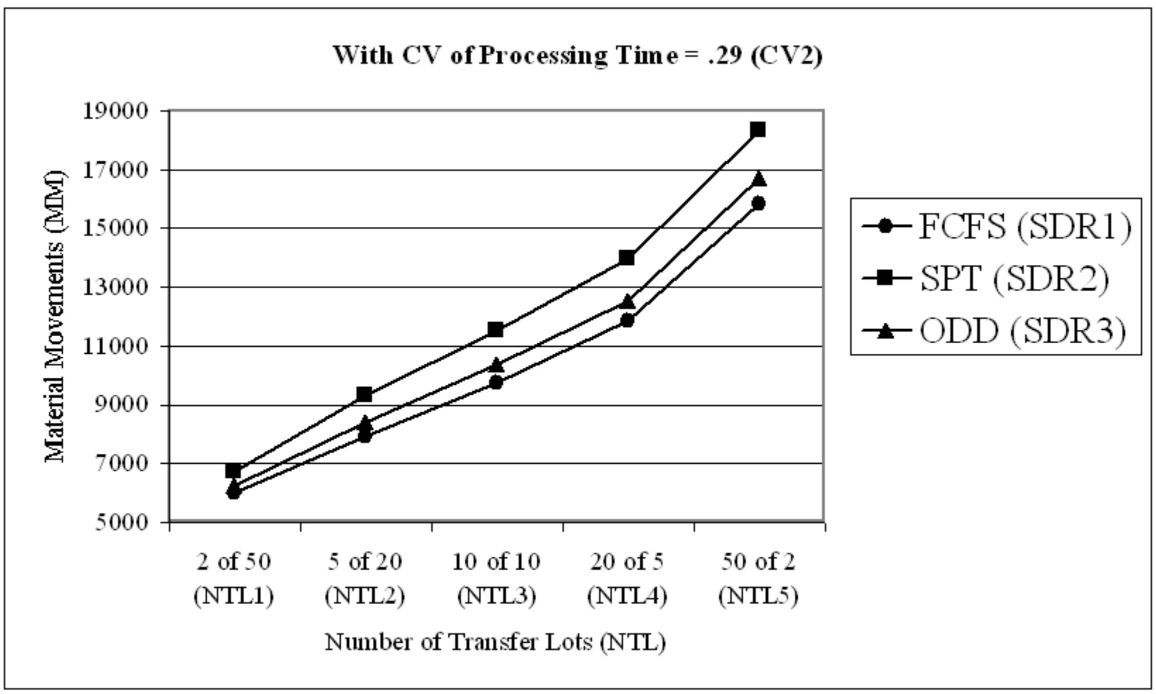


Figure 38. Material Movements (MM) for Number of Transfer Lots (NTL), Secondary Dispatching Rule (SDR), and CV of Processing Time When Using RFID (TM1)

The relatively poor MM performance of the SPT rule can be explained by the fact that when a job type is selected by the SPT rule, it is because it is most likely to finish quickly at the work center. When there are many small transfer lots moving independently, though, choosing the transfer lot with the smallest processing time for the current work center makes it more likely that the transfer lots for that job type still being processed at the upstream work center will be relatively slow. Transfer lots will need to be repeatedly pulled because the downstream work center processes the units much more quickly than the upstream work center, and thus multiple transfer lots do not have time to accumulate at the upstream work center to be pulled downstream in a single material movement.

The relatively good MM performance of the FCFS rule can be explained by the fact that when a job type is selected by the FCFS rule, it is because it has been waiting the longest for processing. Because it has been waiting for a relatively long period of time, it is likely that "trailing" transfer lots for that job type have had time to be processed, so even if they are at an upstream work center, they can be pulled together in a single material movement.

The **key findings related to section 5.4.2** can be summarized as follows:

The material movements (MM) ANOVA for the full experimental design (Figure 30), as well as a follow-up MM ANOVA just using the RFID (TM1) treatments, indicate an interaction involving the extent of lot streaming, choice of secondary dispatching rule, and CV of processing time (NTL*SDR*CV), statistically significant at $p<.001$. Figure 38 shows that at each of the NTL levels, the FCFS rule (SDR1) is best (has the lowest

MM value), followed by ODD (SDR3) and SPT (SDR2), statistically significant at p<.001. Figure 38 also illustrates that the difference in MM between each of the dispatching rules grows between NTL1 and NTL5, statistically significant at p<.001. *The increase in the number of material movements is sensitive to the interaction of the operating policies used (e.g., the secondary dispatching rule) and process changes that might be made as a result of RFID's enabling characteristics (e.g., more lot streaming made possible by RFID's enhanced traceability). From the perspective of material movements, the choice of secondary dispatching rule becomes more critical when RFID is used with extensive amounts of lot streaming (e.g., NTL5).*

5.4.3 Follow-up analysis to Hypothesis 4 to tie together the performance trade-offs when using RFID with increased lot streaming

Motivated by the desire to find conditions where gains can be achieved in mean flow time (MFT) and proportion tardy (PT) by using RFID (TM1) with increased lot streaming (higher NTL) without drastic increases in material movements (MM), Figure 39 combines factors from several of the insights discussed thus far. It shows that improvements in MFT and PT are possible without a severe tradeoff in increased MM when RFID and increased NTL are used with a medium or high SPR ratio (SPR2 or SPR3) and a low CV of processing time (CV1). For example, even with the diminishing returns of increased lot streaming, the decrease in MFT when moving from NTL4 to NTL5 is still statistically significant at p<.001 for each of SPR1, SPR2, and SPR3. The decrease in PT when moving from NTL4 to NTL5 is statistically significant at p<.001, p<.001, and p<.01, for SPR1, SPR2, and SPR3, respectively. Although the increases in MM when moving from NTL4 to NTL5 are statistically significant at p<.001 for each of SPR1 - SPR3, the percentage increase when moving from the NTL1 baseline to NTL5 is 251.0 percent with SPR1, the increase from the NTL1 baseline of SPR2 is only 38.9 percent, and the increase from the NTL1 baseline of SPR1 is only 13.6 percent.

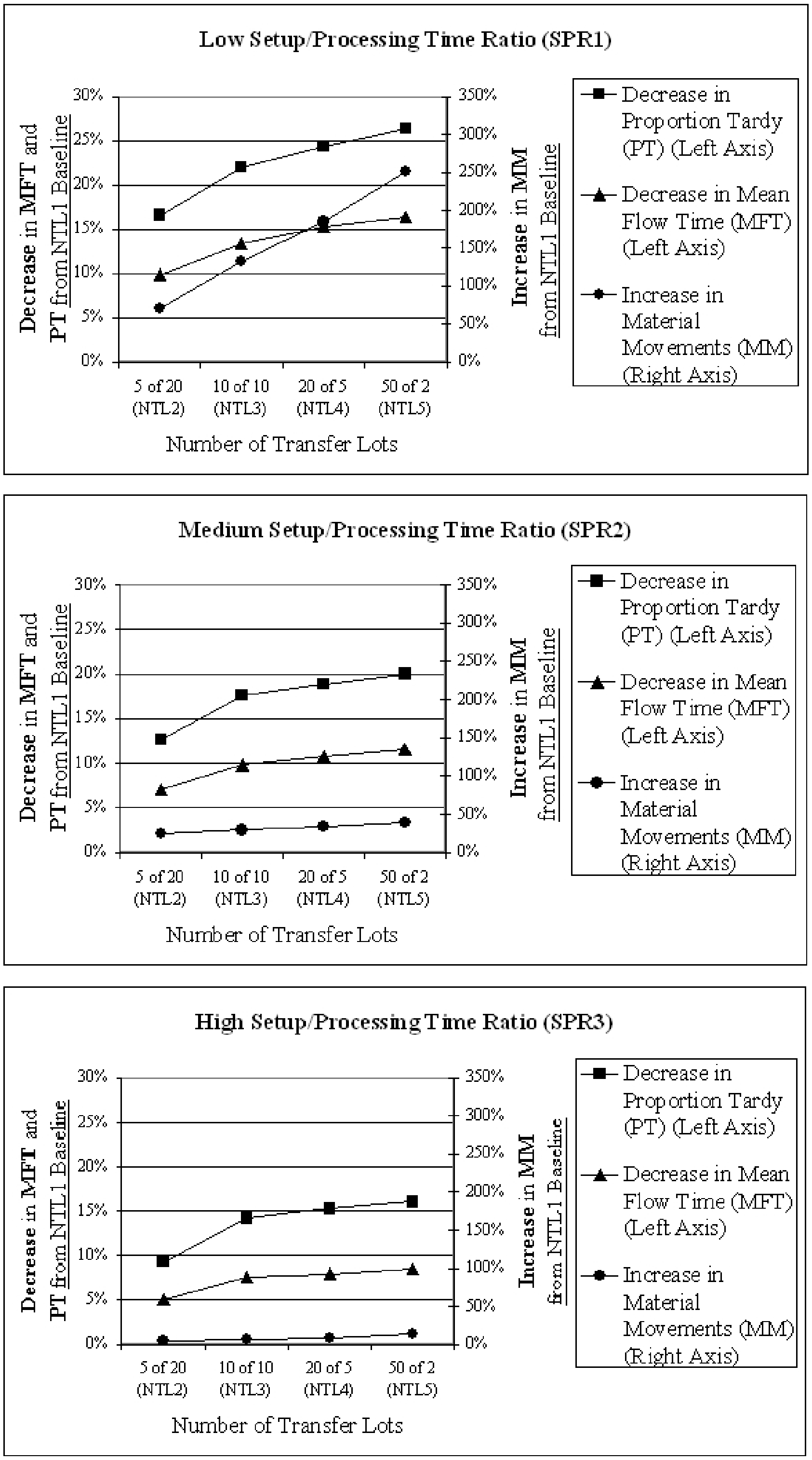


Figure 39. Decrease in Mean Flow Time (MFT) and Proportion Tardy (PT), Increase in Material Movements (MM) With Increased Number of Transfer Lots (NTL) When Using RFID (TM1) and a Low CV of Processing Time (CV1)

Figure 40 plots the same conditions as used with Figure 39, except with a high CV of processing time (CV2). Particularly for SPR1 and SPR2, the improvement in MFT and PFT performance with CV2 in Figure 40 is not as good compared to CV1 in Figure 39, and the increase in MM is more pronounced, although there is still substantial improvement. For both SPR1 and SPR2, the *raw* MFT, PT, and MM values (not comparing to NTL baselines and converted to percentages) are statistically higher ($p<.001$) at CV2 compared to the corresponding values at CV1 (note that higher *raw* MFT, PT, and MM values are worse).

The analysis and discussion for Figure 39 and Figure 40 illustrate that the tradeoff between mean flow time (MFT) and proportion tardy (PT) versus material movements (MM) with RFID-enabled increased lot streaming (NTL) is not nearly as severe when using medium and high SPR ratios (e.g., SPR2 and SPR3), and particularly when the CV of processing times between work centers is also low (e.g., CV1). Companies are frequently advised in the JIT and lean literatures to reduce setup times, but this is not always practically possible. Figure 39 and Figure 40 show that some of the benefits of JIT and lean (reduced flow times and better customer service) can be achieved even with moderate and high setup times (e.g., SPR2 and SPR3) when using extreme lot streaming (e.g., NTL5) that is enabled by RFID (TM1) that facilitates the flow and traceability of smaller lot sizes than were previously possible. Especially in highly competitive industries, the incremental improvement in MFT and PT when using RFID to increase lot streaming can be practically significant even at the most extreme NTL levels, and the costs in material movements will not necessarily be overwhelming in comparison (when the SPR ratios are moderate or high, as with SPR2 and SPR3).

The **key findings related to section 5.4.3** can be summarized as follows:

The improvement in mean flow time (MFT) and proportion tardy (PT) for medium (SPR2) and high (SPR3) setup/processing time ratios when moving from the NTL4 to NTL5 level of lot streaming is statistically significant at no more than $p<.01$. For both SPR1 and SPR2, the *raw* MFT, PT, and material movement (MM) values (not comparing to NTL baselines and converted to percentages) are statistically higher ($p<.001$) at CV2 compared to the corresponding values at CV1 (note that higher *raw* MFT, PT, and MM values are worse). Although the tradeoff of increased material movements (MM) when moving from NTL4 to NTL5 is statistically significant at $p<.001$ for each of SPR1 - SPR3, when the CV is low (e.g., CV1), the percentage increase when moving from the NTL1 baseline to NTL5 is 251.0 percent with SPR1, the increase from the NTL1 baseline of SPR2 is only 38.9 percent, and the increase from the NTL1 baseline of SPR1 is only 13.6 percent. *The trade-offs associated with RFID and related process changes (e.g., improvements in mean flow time and proportion tardy versus increases in the number of material movements as a result of increased lot streaming enabled by RFID's traceability) are sensitive to the operating conditions (e.g., the setup/processing time ratio and CV of processing time).*

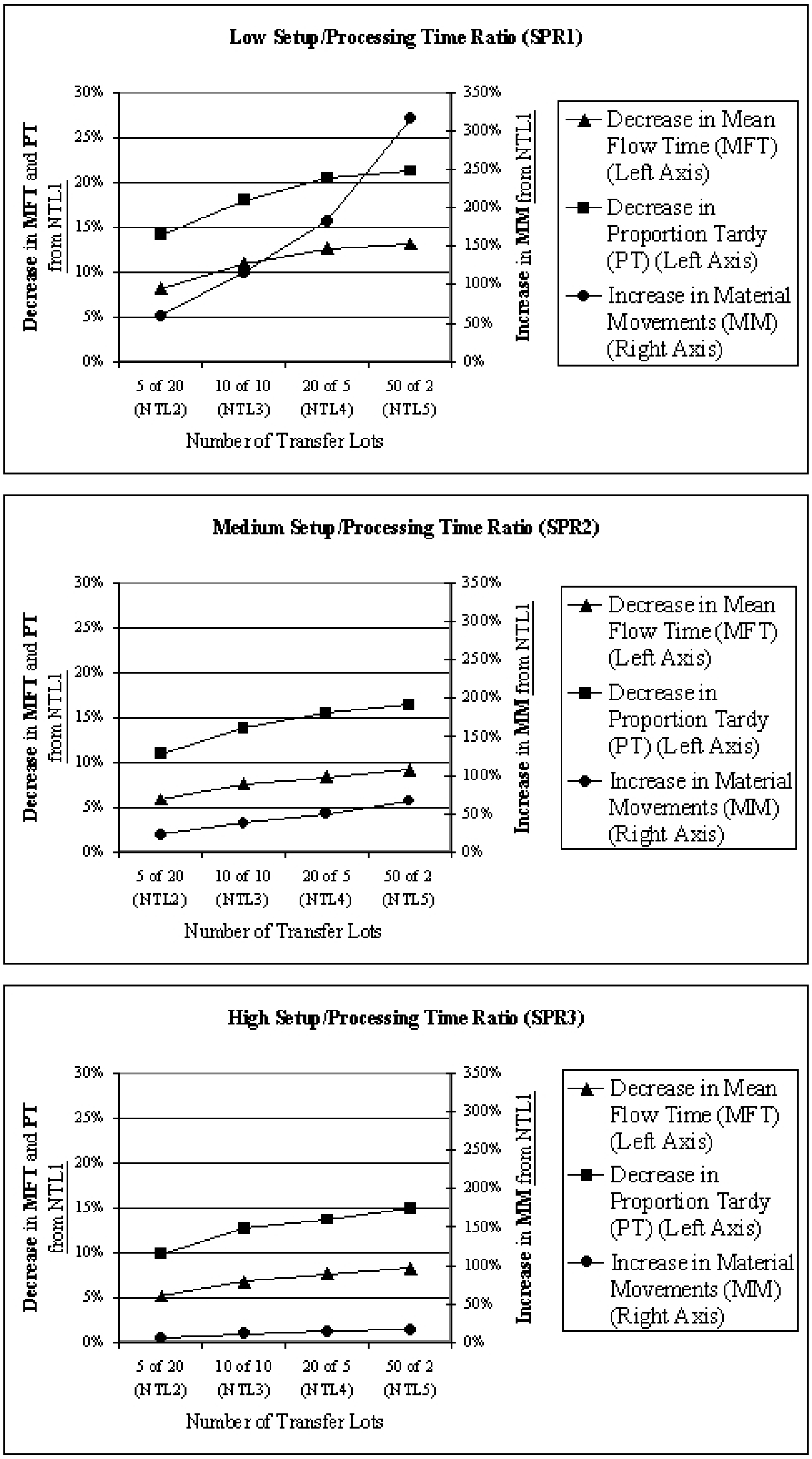


Figure 40. Decrease in Mean Flow Time (MFT) and Proportion Tardy (PT), Increase in Material Movements (MM) With Increased Number of Transfer Lots (NTL) When Using RFID (TM1) and a High CV of Processing Time (CV2)

5.4.4 Follow-up analysis to Hypothesis 4 to compare the performance trade-offs of RFID versus bar coding

It is important to note that Figure 39 and Figure 40 show changes in RFID (TM1) performance with increased NTL against an *RFID baseline*. Although Figure 31 and Figure 32 indicated that RFID performance is at least as good as bar coding (TM2 or TM3), and is increasingly better with more lot streaming (higher NTL), those analyses were *aggregated across several factors and levels*. Figure 39 showed specific conditions (SPR2 or SPR3) where RFID seemed to work well with increasing use of lot streaming, but how might bar coding perform under those same conditions? It is worthwhile to compare RFID and bar coding against the same baseline.

Figure 41 compares RFID (TM1) against slow, deterministic bar coding (TM3) when there is a high SPR ratio (SPR3), a low CV of processing time (CV1), loose due dates (K2), and the ODD secondary dispatching rule (SDR3). Loose due dates and the ODD dispatching rule are chosen because they are more likely to result in proportion tardy (PT) performance that is more commonly seen in the real world, as the analysis for Hypothesis 6 will show. The baseline for all comparisons is when slow, deterministic bar coding (TM3) is used with 2 transfer lots of 50 units (NTL1), so the points for *both* plots of Figure 41 represent the percent performance changes that result when using some combination of increased lot streaming (higher NTL) and/or RFID (TM1) as an alternative.

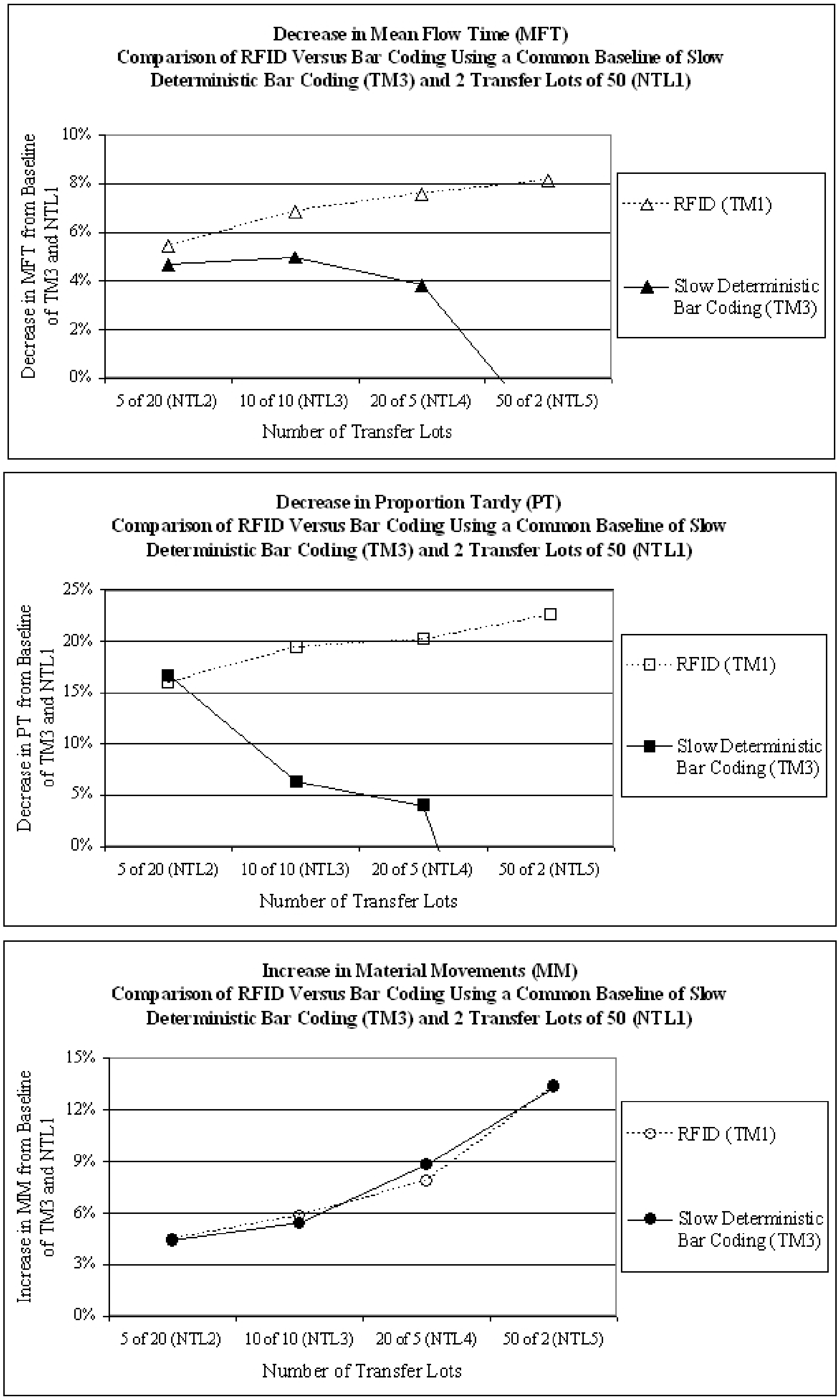
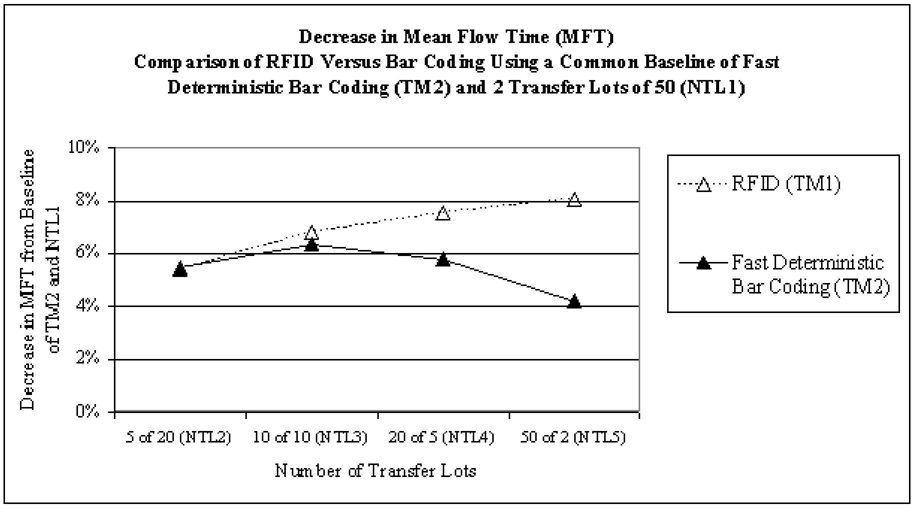
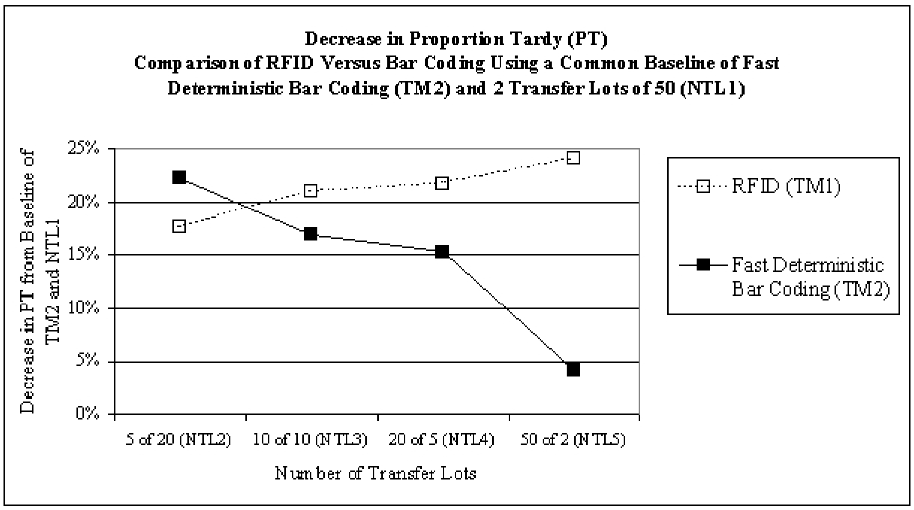


Figure 41. Comparison of RFID (TM1) with Slow, Deterministic Bar Coding (TM3) When There Is a High Setup/Processing Time Ratio (SPR3), a Low CV of Processing Time (CV1), Loose Due Dates (K2), and the ODD Dispatching Rule (SDR3)

At a moderate level of lot streaming (NTL3), the difference between RFID (TM1) and slow deterministic bar coding (TM3) is statistically significant at $p<.001$ for mean flow time (MFT), and at $p<.01$ for proportion tardy. From a qualitative perspective, the initial improvement in MFT and PT and increase in MM for each of the data collection mechanisms (both TM1 and TM3) is similar when 5 transfer lots of 20 (NTL2) are used, but the use of further lot streaming results in clearly better performance for RFID compared to bar coding. For example, RFID (TM1) at NTL5 results in a 10.8 percent improvement in MFT and a 22.6 percent improvement in PT compared to the baseline, whereas the greatest improvement for bar coding (TM2) is 8.3% for MFT (at NTL4) and 16.8 percent for PT (at NTL2). Thus, Figure 41 shows that the MFT and PT versus MM performance trade-off for RFID (TM1) with increasing lot streaming (higher NTL) is good relative to the data collection alternative of slow bar coding (TM3).

The previous results may make one wonder if RFID will always perform better than bar coding, particularly with increased lot streaming (higher NTL). Figure 42 is similar to the previous comparison for Figure 41, except this time fast deterministic bar coding is used (TM2). The baseline for all comparisons is when fast, deterministic bar coding (TM2) is used with 2 transfer lots of 50 units (NTL1), so the points on the graph represent the percent performance changes that result when using some combination of increased lot streaming (higher NTL) and/or RFID (TM1) as an alternative.





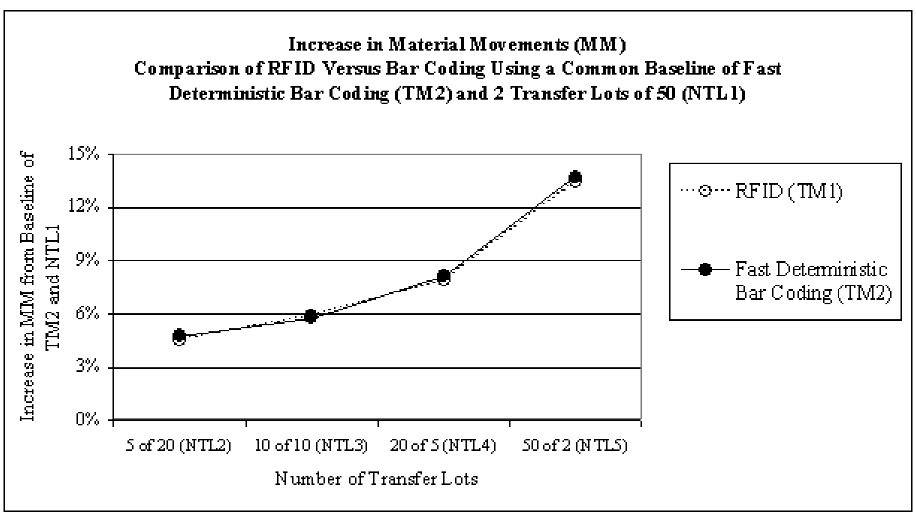


Figure 42. Comparison of RFID (TM1) with Fast, Deterministic Bar Coding (TM2) When There Is a High Setup/Processing Time Ratio (SPR3), a Low CV of Processing Time (CV1), Loose Due Dates (K2), and the ODD Dispatching Rule (SDR3)

Figure 42 shows that mean flow time (MFT) performance is initially very similar between RFID (TM1) and fast bar coding (TM2), but gradually grows more distinct with increased lot streaming (higher NTL). For example, RFID (TM1) at NTL5 results in a 8.1 percent improvement in MFT compared to the baseline, whereas the greatest improvement for bar coding (TM2) is 6.4% at NTL3; the difference between the two respective best cases is statistically significant at $p<.01$. The initial decrease in proportion tardy from 2 transfer lots of 50 (NTL1) to 5 lots of 20 (NTL2) with fast bar coding (TM2) is larger than the decrease in PT with RFID (TM1) from NTL1 to NTL2. In fact, it is not until 50 transfer lots of 2 units (NTL5) that RFID provides PT performance that is superior to fast deterministic bar coding with 5 lots of 20 (NTL2), and even then it is not statistically significant at $p<.10$. Material movements are roughly equal between the two tracking mechanisms (TM1 and TM2); for example, at NTL5, the differences are not statistically different at $p<.10$.

Thus, Figure 42 shows that bar coding might be more appropriate than RFID in some circumstances (e.g., when the bar coding reading is fast, as with TM2, and the SPR ratio is high, as with SPR3), particularly if extreme lot streaming (NTL5) is not used. Extreme lot streaming might not be used if the impact on material movements is perceived to be disproportionately costly and thus prevents splitting jobs into many transfer lots. Figure 42 also shows that when evaluating RFID, it is not only important to observe that performance gets better when RFID is used with increased lot streaming (higher NTL), but RFID needs to be compared against data collection alternatives such as bar coding for the specific operating conditions (e.g., the setup/processing time ratio).

It should be noted that the proportion tardy (PT) performance for bar coding (TM2) is likely better relative to RFID (TM1) in this scenario because later due dates for bar coding were assigned based on the need to spend time tracking each transfer lot. In other words, the bar coding jobs had slightly more time to be completed compared to the corresponding RFID jobs. In many cases this will be an appropriate assumption, because a company would ordinarily want to set due dates based on the *total* work content, including the time spent for tracking. If the due dates used were the same in both scenarios, the PT performance for RFID would presumably be statistically and practically better than bar coding at all levels of lot streaming.

The previous series of results motivate a comparison of RFID (TM1) versus fast bar coding (TM2) with a medium setup/processing time ratio (SPR2); the other conditions are the same as in the previous scenario for Figure 42. Figure 43 shows much better PT performance for RFID compared to fast bar coding relative to the previous scenario for Figure 42, even at low and moderate levels of lot streaming (significant at $p<.05$ for NTL2 and $p<.01$ for NTL3). MFT performance with RFID is still at least as good as bar coding performance; at NTL3, the difference is statistically significant at $p<.001$, and like PT, the gap grows larger with higher levels of lot streaming (increased NTL). There are slightly more material movements with RFID than with fast bar coding (e.g., statistically significant at $p<.01$ at NTL3), but even with the difference growing with increased NTL, the difference at NTL5 is still less than 1.2 percent. Because of the way that fast bar coding (TM2) and slow bar coding (TM3) are defined, the former should always result in better MFT and PT performance than the latter. Thus, relative to the previous scenario in Figure 42 where the SPR ratio was high (SPR3), RFID (TM1) in this scenario is much more attractive compared to both fast bar coding (TM2) and slow bar coding (TM3) when the SPR ratio is moderate (SPR2). When considering the relative superiority of RFID to bar coding, moderate levels of the SPR ratio might be the “sweet spot” for RFID use, even when the bar code reads are fast and the most extreme forms of lot streaming (e.g., NTL4 and NTL5) are not used.

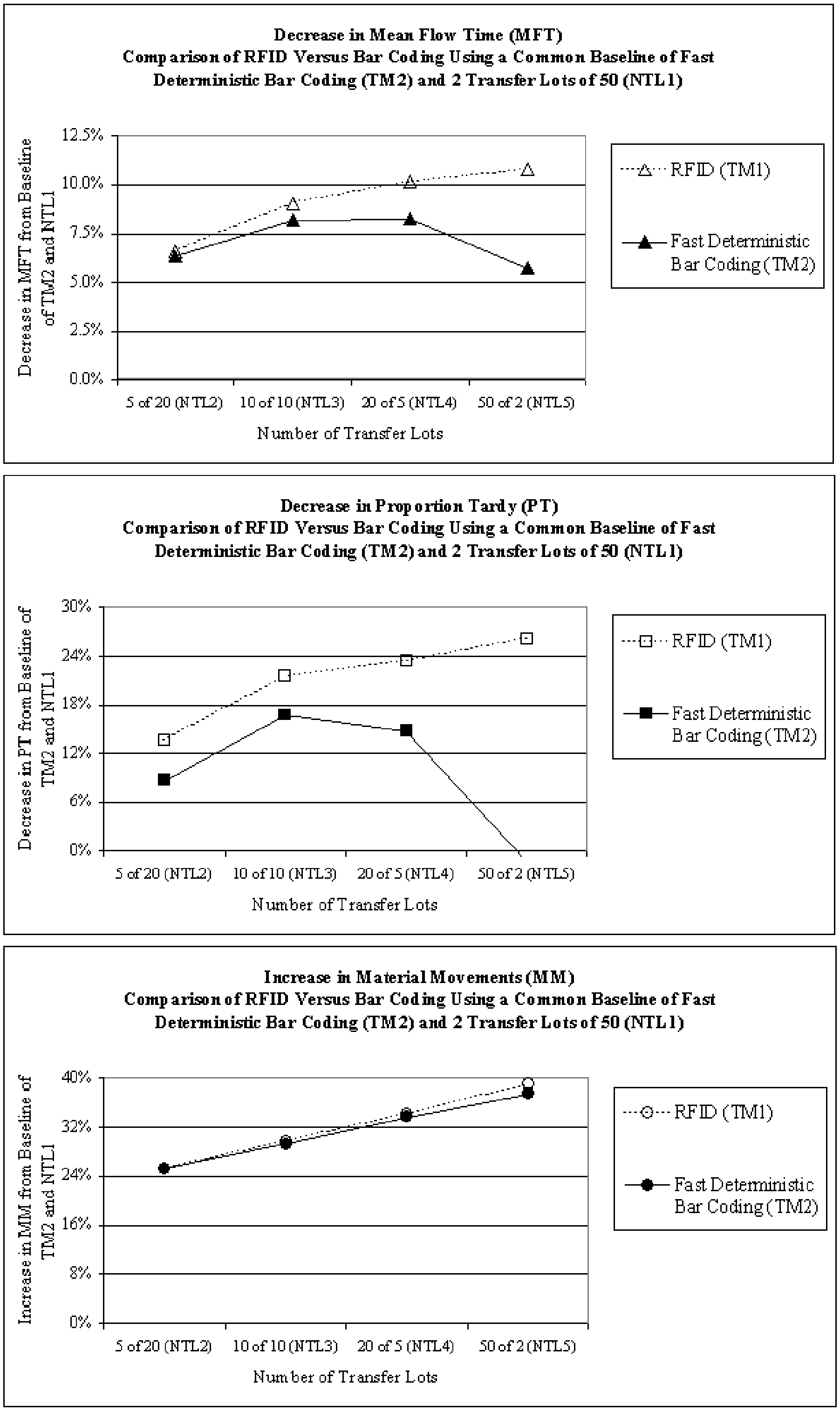


Figure 43. Comparison of RFID (TM1) with Fast, Deterministic Bar Coding (TM2) When There Is a Medium Setup/Processing Time Ratio (SPR2), a Low CV of Processing Time (CV1), Loose Due Dates (K2), and the ODD Dispatching Rule (SDR3)

The **key findings related to section 5.4.4** can be summarized as follows:

At a moderate level of lot streaming (NTL3), the difference between RFID (TM1) and slow deterministic bar coding (TM3) is statistically significant at $p<.001$ for mean flow time (MFT), and at $p<.01$ for proportion tardy (PT), when there is a high setup/processing ratio (SPR3), low CV of processing time (CV1), loose due dates (K2), and the ODD dispatching rule is used (SDR3). The difference between RFID and bar coding grows even more significant with increased lot streaming (higher NTL). When comparing RFID against fast deterministic bar coding (TM2) when there is a high setup/processing ratio (SPR3) and the conditions are otherwise the same, the best MFT performance for RFID is statistically better at $p<.01$ for mean flow time (MFT) compared to the best bar coding performance, but the best PT performance for each (bar coding and RFID) are not statistically significant at $p<.10$. When conditions are the same as the previous examples, except with a moderate setup/processing time ratio (SPR2), RFID PT performance compared to fast bar coding (TM2) is better even at low and moderate levels of lot streaming (significant at $p<.05$ for NTL2 and $p<.01$ for NTL3). MFT performance with RFID is at least as good as bar coding performance; at NTL3, the difference is statistically significant at $p<.001$, and as with PT, the gap grows larger with higher levels of lot streaming (increased NTL). In all three of the aforementioned scenarios (TM1 versus TM3 at SPR3, TM1 versus TM2 at SPR3, and TM1 versus TM2 at SPR2), the difference in material movements between RFID and bar coding is either not statistically significant at $p<.10$, or is not practically very large (e.g., less than 1.2 percent).

The "takeaway" for managers is that RFID and increased lot streaming might be most appropriate:

- *when setup times are moderate (e.g., SPR2), regardless of whether the data collection alternative (e.g., bar coding) is relatively fast or slow,*
- *or when setup times are high (e.g., SPR3) and the data collection alternative is relatively slow.*

The analysis for section 5.4.3 showed that material movements can increase by over 200 percent when setup times are low (e.g., SPR1) and the extent of lot streaming is increased from low (e.g., NTL1) to high (e.g., NTL5). Such increases in material movements will not be feasible for many companies, even if high levels of automated material handling are used. Together with the analysis for Hypothesis 2, which showed that RFID and bar coding have nearly identical performance when low levels of lot streaming are used (which is necessary to avoid excessive material movements with low SPR ratios), the combined results show that it will often not make sense to use RFID when the SPR ratio is low (e.g., SPR1), because bar coding can offer nearly the same performance, at presumably less cost.

5.5 Hypothesis 5: Mean flow time (MFT) and proportion of jobs tardy (PT) should increase (be worse) with more read batching (with greater RB). Stated more formally, increasing levels of RB should result in higher MFT and PT, statistically significant at no more than $p < .10$.

The MFT and PT ANOVAs in Figure 28 and Figure 29 suggest that read batching has a statistically significant effect. Post-hoc tests for MFT indicate that the difference between RB1 and RB2 is significant ($p<.05$), between RB1 and RB3 is significant (p.<001), and between RB2 and RB3 is significant ($p<.01$). Post-hoc tests for PT indicate that the difference between RB1 and RB2 is not significant ($p>.10$), between RB1 and RB3 is significant (p.<001), and between RB2 and RB3 is significant ($p<.05$). Examining tables and plots of the main effects for read batching (Figure 44 and Figure 45) suggests that the practical significance is very small (e.g., the difference in the dependent variables with RB1 and RB3 is less than one percent). It should also be noted that the statistically significant interaction effects involving read batching were also examined and found to have little or no practical significance. Figure 28 and Figure 29 show that read batching did not did not combine with the tracking mechanism (TM) factor in any significant combination, so the results are essentially the same regardless of whether RFID or bar coding is used. Thus, while Hypothesis 5 is statistically true, read batching seems to have a small practical effect (less than one percent difference in mean flow time and proportion tardy), regardless of the use of RFID versus bar coding.

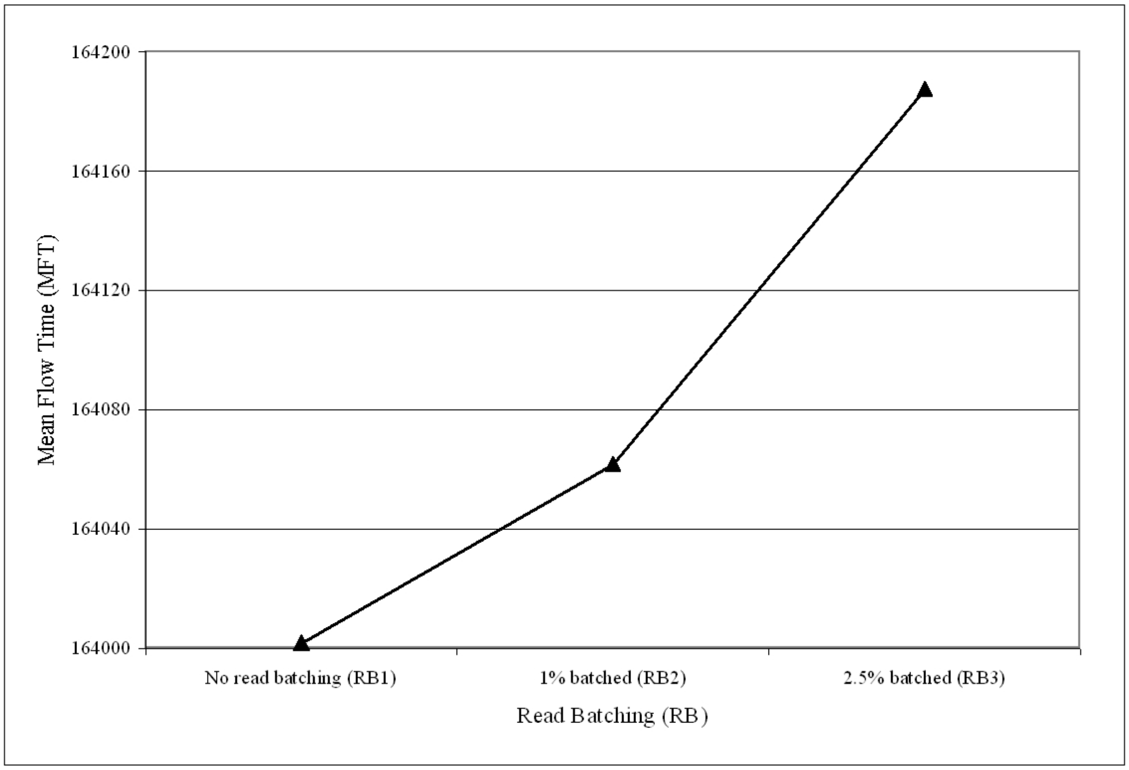


Figure 44. Mean Flow Time (MFT) for Read Batching (RB)

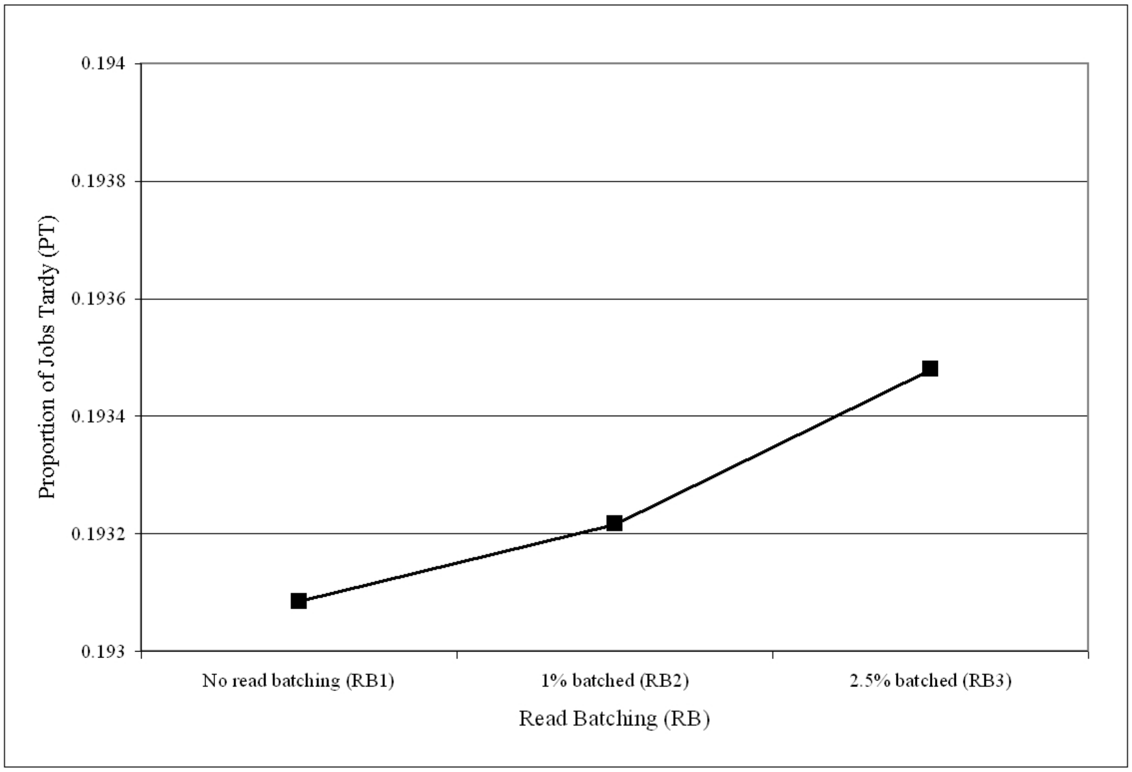
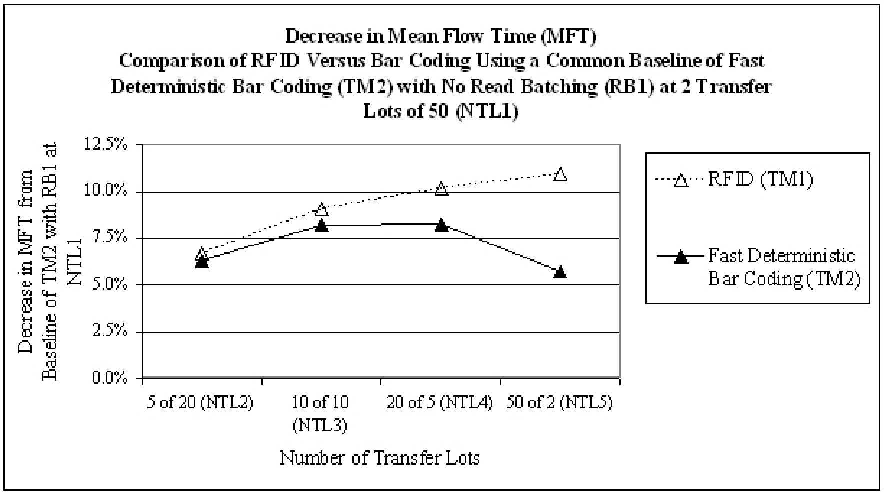
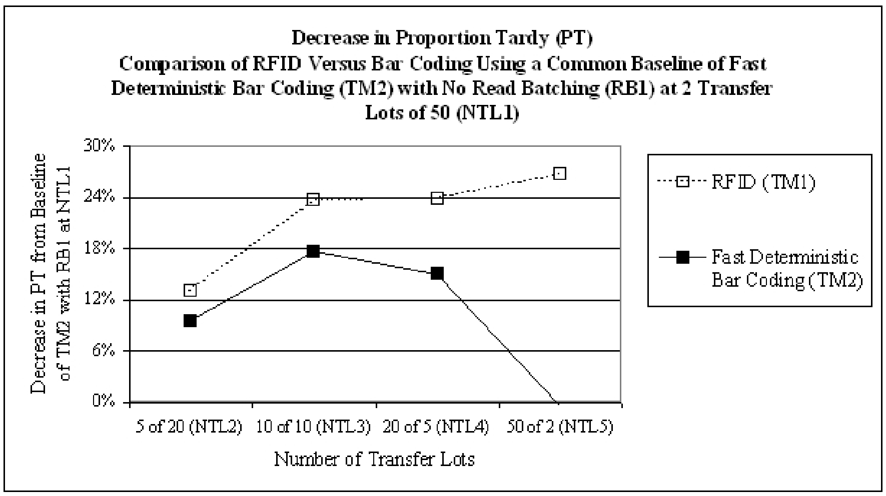


Figure 45. Proportion Tardy (PT) for Read Batching (RB)

As one example of the lack of practical impact from read batching, consider that Chapter 3 noted that read batching can be used as a measure of the impact of RFID read reliability. Some RFID advocates look to RFID's low-variable cost, continuous, automated data collection as a way to avoid process problems from unreliable labor. Despite this, several sources have cited low read reliability rates for RFID systems. While such problems are often attributed to technical issues that are expected to eventually be resolved, could poor reliability change a condition where RFID is ideal to one where bar coding would be preferred?

To examine this issue of the impact of reliability, Figure 46 is based on the same RFID-ideal conditions as Figure 43 (SPR2, CV1, K2, and the ODD dispatching rule), except the RFID scenario is modeled to use read batching (RB3), whereas the fast bar coding scenario is modeled to use no read batching (RB1). The baseline used for all comparisons in Figure 46 is fast bar coding (TM2) with no read batching (RB1) and 2 transfer lots of 50 units (NTL1), so the solid points on the graph represent relative changes in performance when using increased lot streaming, but otherwise the same conditions as the baseline (fast bar coding with no read batching). In contrast, the hollow points on the graph represent relative changes in performance against the baseline, but the changes are due to a combination of the fact that RFID (TM1) is used instead of fast bar coding (TM3), read batching (RB3) is present (no read batching is present in the baseline scenario), and increased lot streaming is used (there is a higher NTL compared to the baseline).





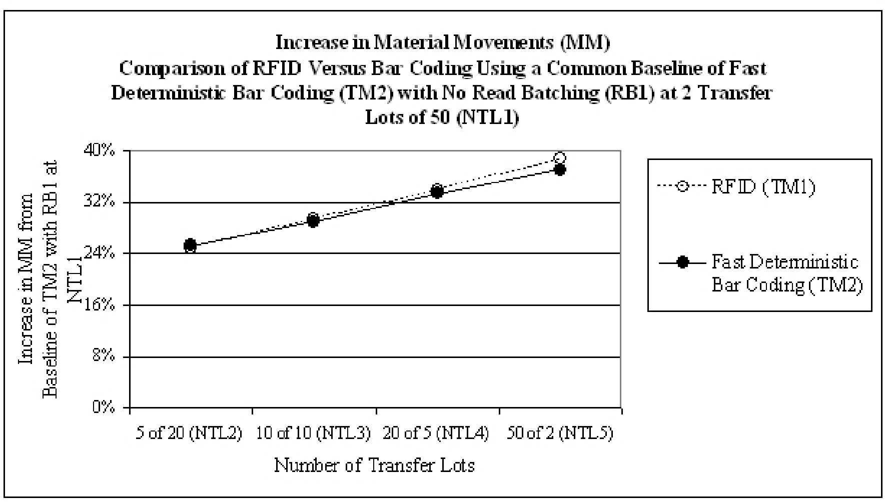


Figure 46. Comparison of RFID (TM1) with Read Batching (RB3) Versus Fast, Deterministic Bar Coding (TM2) with No Read Batching (RB1) When There Is a Medium Setup/Processing Time Ratio (SPR2), a Low CV of Processing Time (CV1), Loose Due Dates (K2), and the ODD Dispatching Rule (SDR3)

Figure 46 shows that even under those conditions where RFID should be hindered by the worse process conditions caused by the read batching, RFID can still provide better mean flow time (MFT) and proportion tardy (PT) performance than bar coding, particularly when intermediate and high levels of lot streaming (e.g., NTL4 and TL5) are used. At NTL3, RFID (TM1) has significantly better MFT than fast bar coding (TM2), $p<.01$, and also significantly better PT, $p<.10$, and the gap grows wider with increased lot streaming (higher NTL). Figure 46 illustrates that even if RFID read reliability is initially lower than bar coding (e.g., because of technical limitations or implementation problems with the newer technology), RFID can still provide better MFT and PT performance than bar coding. This is congruent with a report produced by EPCglobal (2006), that found that value in consumer packaged goods supply chains could still be obtained from RFID even with read rates substantially less than 100 percent. Thus, while our results show that RFID may not always be appropriate, even with imperfect read rates (e.g., RB3) RFID may still be a viable candidate in process improvement projects, depending on the availability of capable data tracking alternatives and the environment in which it is used.

The reason that read batching (RB) does not have more statistical significance and a larger percentage impact on mean flow time (MFT) and proportion tardy (PT) between treatment levels (e.g., RB1 versus RB2) might be similar to the issues associated with deterministic versus stochastic bar coding (see Hypothesis 1 and its comparison of TM2 versus TM4 and TM3 versus TM5). One reason might be that read batching will only hurt performance if the downstream work center is idle. With 80 percent utilization, even if the reading of an upstream transfer lot is batched, it may not matter if the downstream work center is busy. Furthermore, when there is a low setup/processing time ratio (e.g., SPR1), the penalty for switching between job types is relatively non-severe, and so there is relatively little penalty even if upstream read batching causes extra setups downstream. When the SPR ratio is high (e.g., SPR3), there is a good chance that even if an upstream transfer lot has its read batched, the downstream work center will be busy performing a setup on a leading transfer lot of the same job type, and will not finish processing that leading lot until the upstream lot has finally been read and is ready to be moved. Future research may want to examine in more detail the conditions with which read batching may have an impact.

The **key finding related to the analysis for Hypothesis 5** can be summarized as follows:

> Tests for MFT indicate that the difference between RB1 and RB2 is significant ($p<.05$), between RB1 and RB3 is significant ($p.<001$), and between RB2 and RB3 is significant ($p<.01$). Post-hoc tests for PT indicate that the difference between RB1 and RB2 is not significant ($p>.10$), between RB1 and RB3 is significant ($p.<001$), and between RB2 and RB3 is significant ($p<.05$). Examining tables and Figure 44 and Figure 45 shows that even though there is statistical significance, the largest difference in the dependent variable is less than one percent. When comparing RFID (TM1) with high read batching (RB3) versus fast bar coding (TM2) with no read batching (RB1) under the conditions shown in Figure 46, RFID has significantly better MFT than fast bar coding,

p<.01, and also significantly better PT, p<.10, when there is moderate lot streaming (e.g., NTL3) and the gap grows wider with increased lot streaming (higher NTL). Figure 46 illustrates that even if RFID read reliability is lower than bar coding (e.g., as modeled by the higher RB3 read batching factor level for RFID compared to the RB1 level for bar coding), RFID (TM1) can still provide superior mean flow time (MFT) and proportion of jobs tardy (PT) performance compared to bar coding (whether TM2 or TM3). When used in appropriate settings (see Hypothesis 4), the newness of the technology (and associated technical limitations or implementation problems such as read reliability) should not necessarily be a deterrent for investing in RFID. *Even if the relative newness of RFID leads to lower read reliability (e.g., RB3) compared to bar coding because of technology issues that are yet to be resolved, RFID can still be a viable candidate for consideration in process improvement projects (e.g., to enable increased lot streaming that will lead to reduced flow times and proportion tardy)* .

5.6 Hypothesis 6: Mean flow time (MFT) should be best with the shortest processing (SPT) dispatching rule (SDR2). When due dates are tight (K1), then proportion of jobs tardy (PT) should be best for the SPT dispatching rule (SDR2). When due dates are loose (K2), then PT should be best for the earliest operation due date (ODD) dispatching rule (SDR3). Stated more formally, the SPT rule (SDR2) is expected to be statistically better (at no more than p<.10) than FCFS (SDR1) and ODD (SDR3) for MFT. An SDR*K interaction effect is expected to be identified for the proportion of jobs tardy (PT), with the SPT rule (SDR2) being statistically better (at no more than $p<.10$) with tight due dates (K1), and the ODD rule (SDR3) being statistically better (at no more than $p<.10$) for loose due dates (K2).

The ANOVA in Figure 28 indicates there are SDR*CV and SDR*K interactions for MFT ($p<.001$ for both interactions). While SPT is better than the other rules for MFT performance, the difference is more pronounced with higher CV (e.g., CV2), as seen in Figure 45, and higher K (e.g., K2), as seen in Figure 48. Pairwise comparisons of the data used to make Figure 45 indicate that the difference between SPT and ODD is significant at $p<.05$ at CV1, and the difference is significant at $p<.001$ at CV2. Pairwise comparisons of the data used to make Figure 48 indicate that the difference between SPT and ODD is significant at $p<.001$ at both K1 and K2. Figure 28 also indicated other interactions, but examining plots and tables of the numerical results indicate the results were essentially the same (e.g., the SPT rule is statistically better than or equal to the other rules). The various analyses thus provide support for Hypothesis 6.

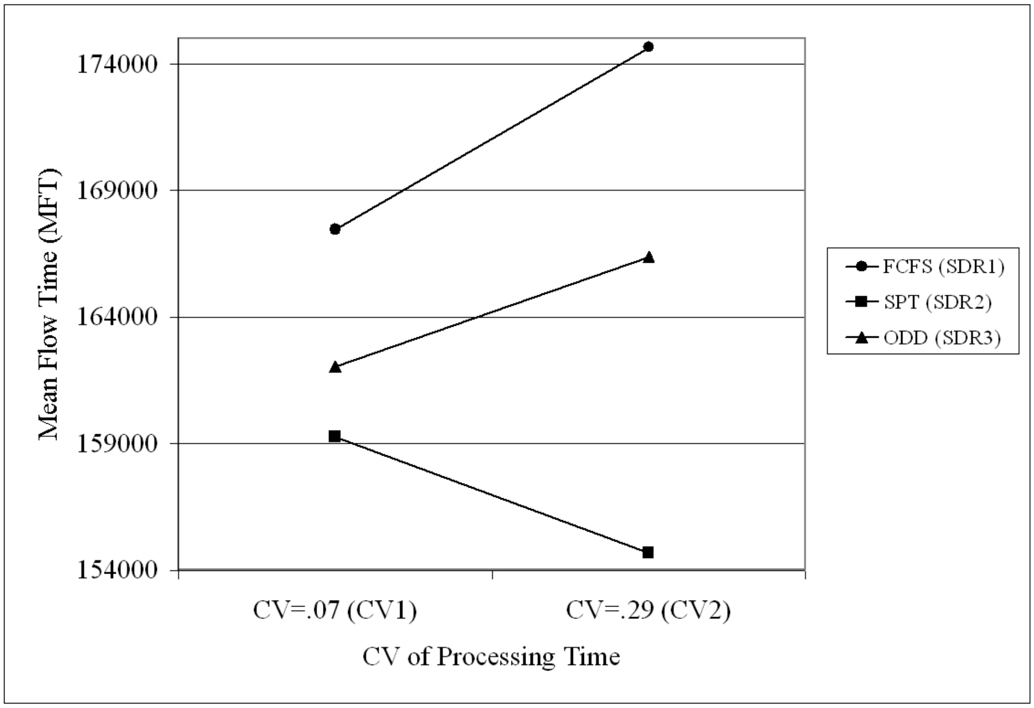


Figure 47. Mean Flow Time (MFT) for Secondary Dispatching Rule (SDR) and CV of Processing Time (CV)

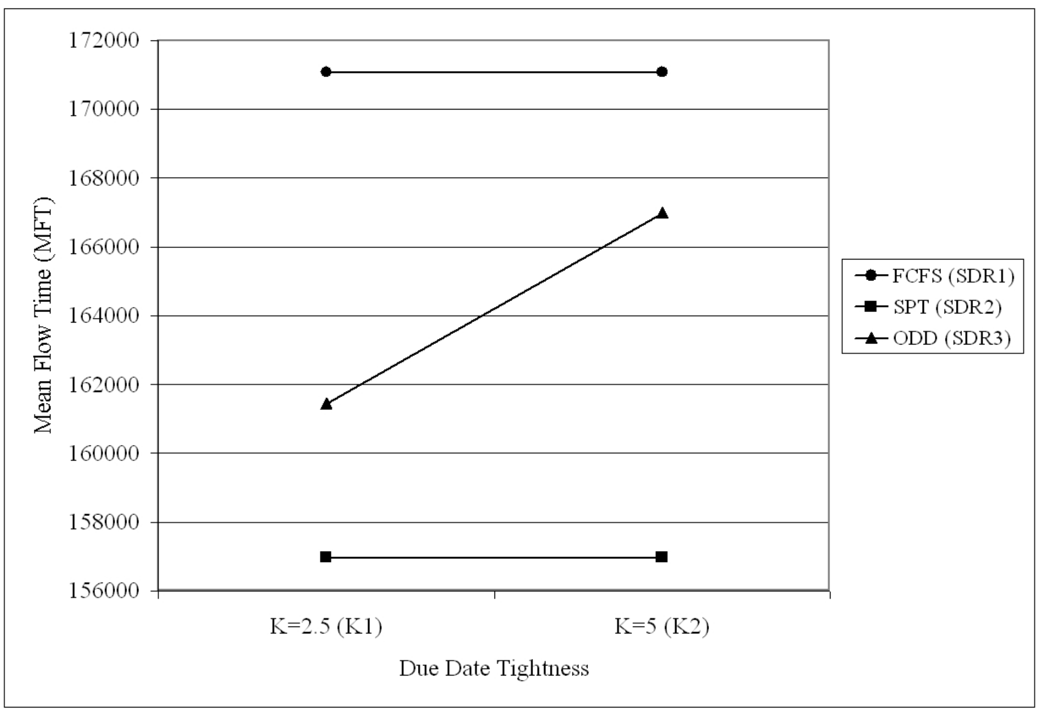


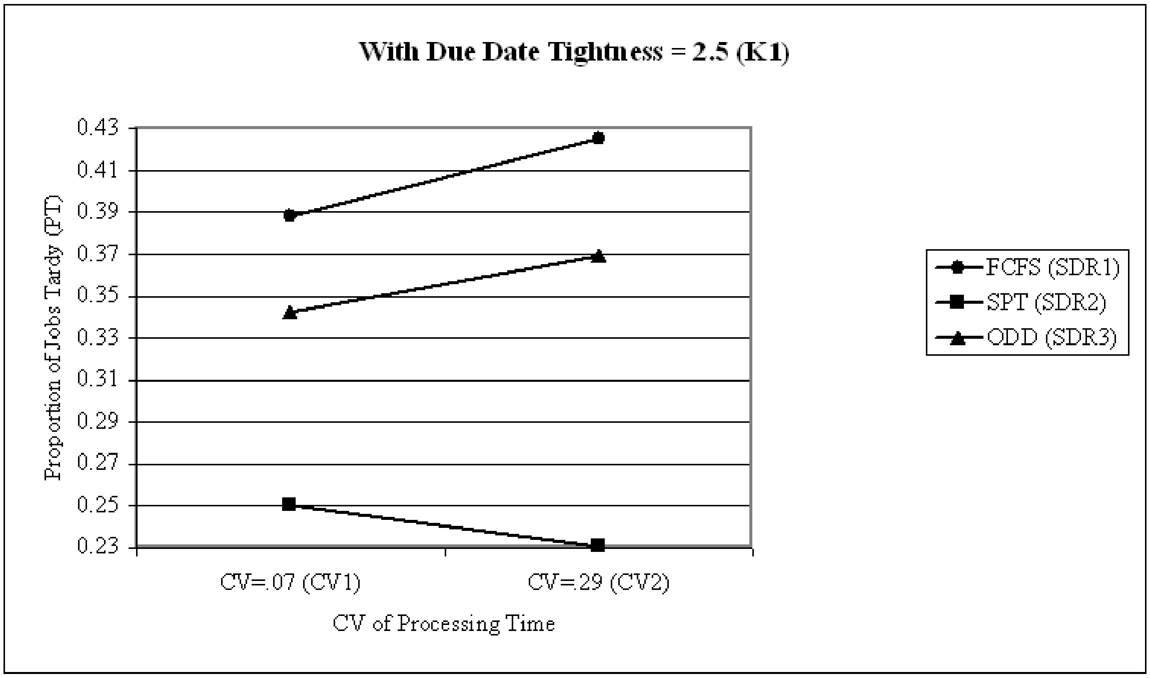
Figure 48. Mean Flow Time (MFT) for Secondary Dispatching Rule (SDR) and Due Date Tightness (K)

It should be noted that the ANOVA for mean flow time (MFT) in Figure 28 indicates that the TM*SDR*CV interaction is not statistically significant at p<.10 and the TM*SDR*K interaction is only marginally statistically significant (p<.10). The TM*SDR*K results are an artifact of the power of the experimental design. Examination of plots for TM*SDR*K show that at each level of TM (i.e., regardless of whether RFID or one of the forms of bar coding is used), the results are qualitatively the same as described above for the SDR*K interaction (and thus there is no practically significant TM*SDR*K interaction, because the performance rankings of the rules and the relative impact of the interactions are the same). In other words, the tracking mechanism for transfer lots (the TM level for RFID and the different bar coding levels) does not substantially affect the interpretation of the above results for Figure 45 and Figure 48.

The takeaway for managers is that regardless of whether bar coding or RFID is used, SPT is better than the other dispatching rules for mean flow time (MFT) performance, but the difference is not always large. For example, with low CV of processing times between work centers (e.g., CV1), the difference between SPT and ODD is 1.72 percent in Figure 47. With tight due dates (e.g., K1), the difference between MFT performance for SPT and ODD is approximately 2.85 percent in Figure 48. These results are compatible with the theory developed in earlier research (Baker, 1984; Jayamohan and Chandrasekharan, 2000) (thus providing validation for this model), but they also extend previous research. As noted in the Chapter 3 discussion of the experimental design, previous lot streaming research that examined the effect of different

SDR rules on MFT did not differentiate between the types of tracking mechanism used (e.g., the TM levels for RFID versus the various forms of bar coding).

The ANOVA in Figure 29 indicates there are SDR*CV, SDR*K, and SDR*CV*K interactions for PT ($p<.001$ for each). In this situation, it is useful to look at the plots for the three-way interaction shown in Figure 49. It can be seen that when the due dates are tight (K1), the SPT rule is best ($p<0.01$ when compared against ODD with pairwise tests for both CV1 and CV2), and that when the due dates are loose (K2), the ODD rule is best for minimizing the proportion tardy ($p<.001$ when compared against FCFS for CV1 and $p<.001$ when compared against SPT for CV2). This is congruent with Hypothesis 6. When due dates are tight (K1), the gap between SPT and ODD is somewhat closer when the CV is low (CV1), and FCFS is the worst secondary dispatching rule regardless of the CV level. Interestingly, PT performance when using the SPT rule is particularly bad when the due dates are loose (K2) and the CV is low (CV1).



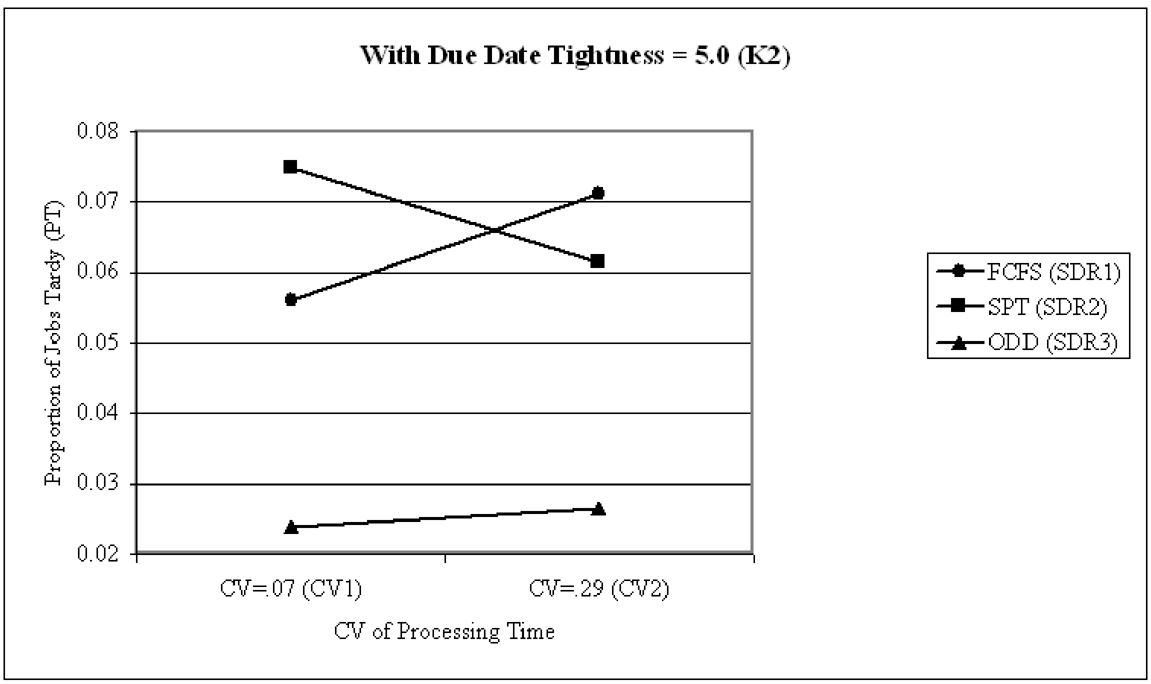
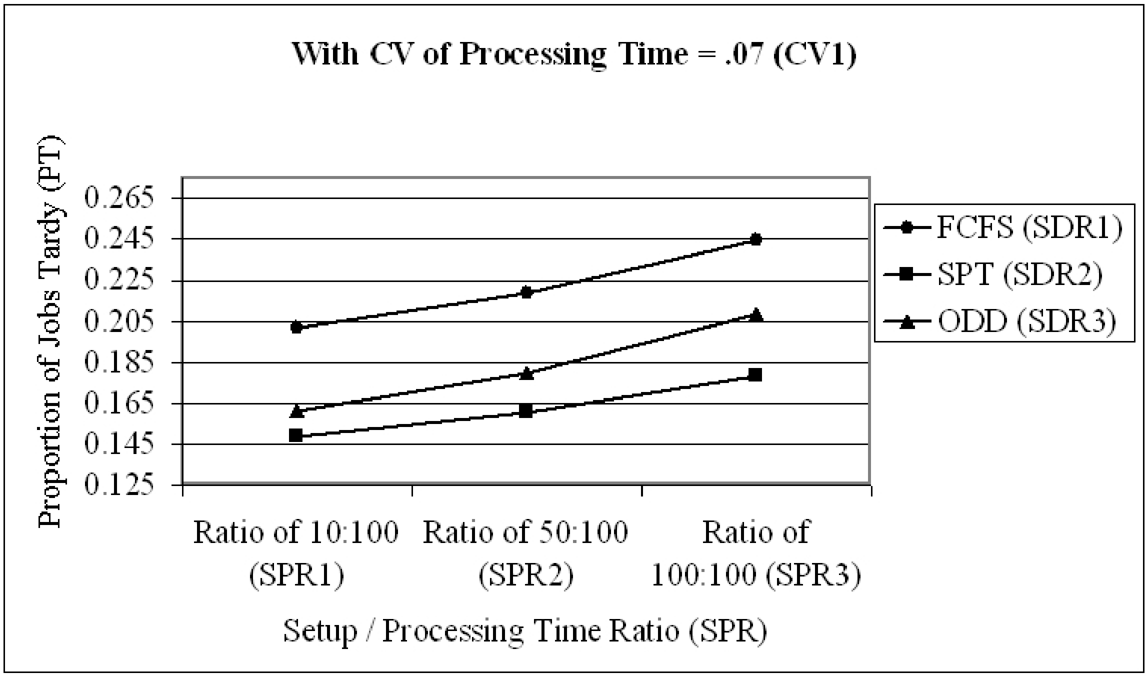


Figure 49. Proportion Tardy (PT) for Secondary Dispatching Rule (SDR), CV of Processing Time (CV), and Due Date Tightness (K)

The ANOVA for PT in Figure 29 also indicates an SPR*SDR*CV interaction ($p<.001$). Figure 50 plots the interaction, which (similar to Figure 49) shows that the PT performance gap between the SPT and ODD secondary dispatching rules at the various setup/processing time ratios is substantially smaller when the CV of processing time is low (CV1). For CV1, the gap is not statistically significant at $p<.10$ for SPR1 and SPR2, and at SPR3, the gap is statistically significant at $p<.10$. In contrast, at CV2, the gap is statistically significant at $p<.001$ at SPR1, and at $p<.001$ for SPR2 and SPR3. Figure 50 also shows that SPT is always as good or better than the other dispatching rules for PT when looking at any combination within the SPR*SDR*CV interaction plot. In contrast, Figure 49's illustration of the SDR*CV*K interaction and the accompanying analysis showed that when due dates are "loose" as opposed to "tight", the ODD rule is best for PT. Which dispatching rule is most likely to be ideal for reducing PT in the "real world"?



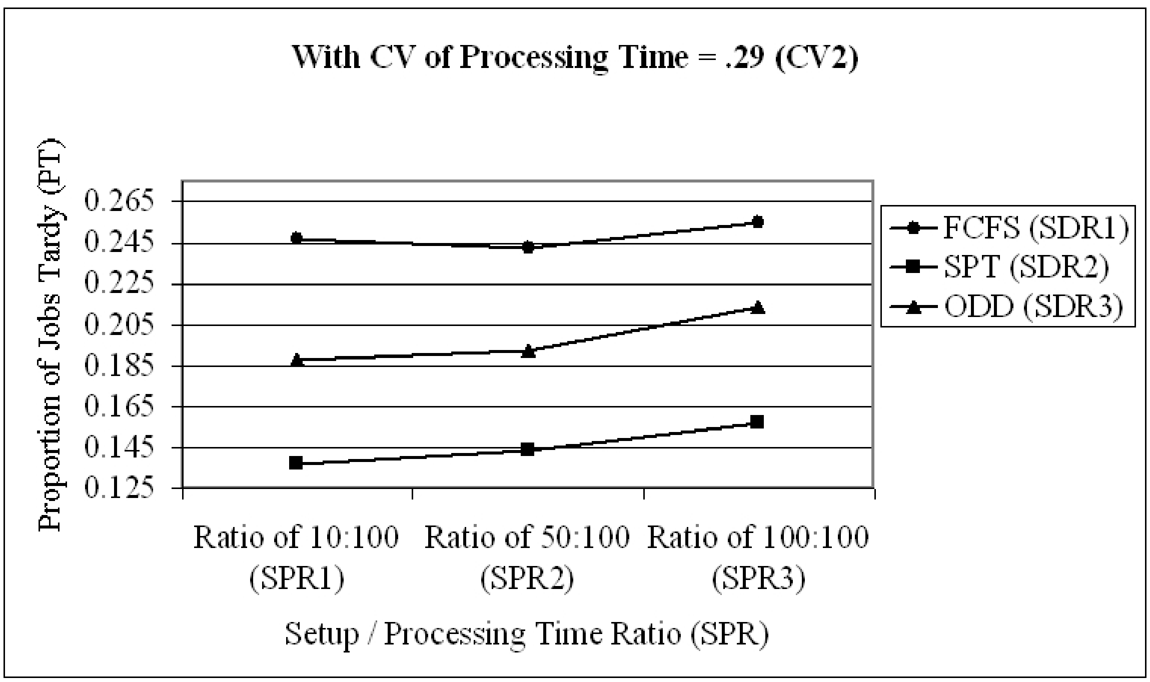


Figure 50. Proportion Tardy (PT) for Setup/Processing Time Ratio (SPR), Secondary Dispatching Rule (SDR), and CV of Processing Time (CV)

Before answering this question, it should be noted that similar to the conclusions for MFT performance, the conclusions regarding the SDR*CV*K and SPR*SDR*CV interactions for PT are the same regardless of whether RFID (TM1) or bar coding (TM2 or TM3) is used. The statistically significant interactions involving TM, SPR, SDR, CV, and K in the ANOVA in Figure 29 were examined, and in each case, the interactions did not exhibit practical significance that meaningfully affected the above (or following) conclusions, such as the relatively performance of the dispatching rules under different scenarios. A special ANOVA (not shown) with TM*SDR*CV*K and TM* SPR*SDR*CV treatment effects was also run, but those interactions were not statistically significant at $p<.10$. Thus, the essential motivations and conclusions are the same regardless of whether looking at the tracking mechanism in aggregate (e.g., TM1-TM5 averaged together) or for a specific tracking mechanism (e.g., individually analyzing any of the RFID or bar coding levels within TM1-TM5).

To answer the question about which dispatching rule is most likely to be ideal for reducing PT in the “real world”, it should be understood that the labels “loose” and “tight” in regards to the discussion of due date setting are relative. Baker and Kanet (1983) observed, “It is unfortunate that little or no empirical research has been done to reveal the actual values of K for different industries. However, several experienced researchers have suggested K=10 to be a good guess of average industrial due date tightness…If we assume an average industry allowance factor of 10 then it would be fair to assume that firms operating with low utilization (80%) would likely be using factors somewhat less than 10…” Thus, Baker and Kanet (1983) used K values of 2.5, 5, 7.5, and 10 when the utilization was 80 percent. In the model used for this dissertation, the K=2.5 level (K1) led to over 30 percent of the jobs being tardy, and even the K=5.0 level

(K2) led to over 2 percent of the jobs being tardy when the best rule (ODD) for that scenario was used (see Figure 49). The K=2.5 level (K1) is useful for comparing with past research, but is probably not as useful for developing conclusions for today's business environments. For many companies, the K=5 (K2) level of customer service would presumably be the minimum acceptable, and so K=5 (K2) level might actually be considered tight by them, particularly when using a dispatching rule that is not ideal for the conditions.

To understand whether ODD or SPT is more appropriate for most companies, Figure 51 provides some insight, by replicating the conditions of Figure 50 (showing the SPR*SDR*CV interaction), except it also fixes the due date tightness level at K2 (such "loose" due dates more likely to lead to realistic tardiness levels). As can be seen in Figure 51, ODD is always better ($p<.001$) than the other dispatching rules for the proportion tardy (PT) metric, regardless of CV and SPR, when realistic due date setting (K2) is used. When realistic due date setting (K2) is used, the SPT rule results in PT that is 2-3 *times* as large as when ODD is used. Although SPT performs better than ODD for the mean flow time (MFT) criterion when loose due dates (K2) are used (at $p<.001$ at CV1 and CV2 for SPR1 and SPR2, at $p<.01$ at CV1 for SPR3, and at $p<.001$ for CV2 at SPR3), an examination of the data underlying Figure 52 shows that MFT for ODD is only approximately 3-5 *percent* more than with the SPT rule with low CV (CV1), and approximately 8-11 *percent* more with high CV (CV2). Thus, while there is a tradeoff between the shortest processing time (SPT) and earliest operation due date (ODD) dispatching rules for mean flow time (MFT) versus proportion of jobs tardy (PT) performance, many companies might find ODD to be more attractive given that it has much better PT performance and only slightly worse MFT performance.

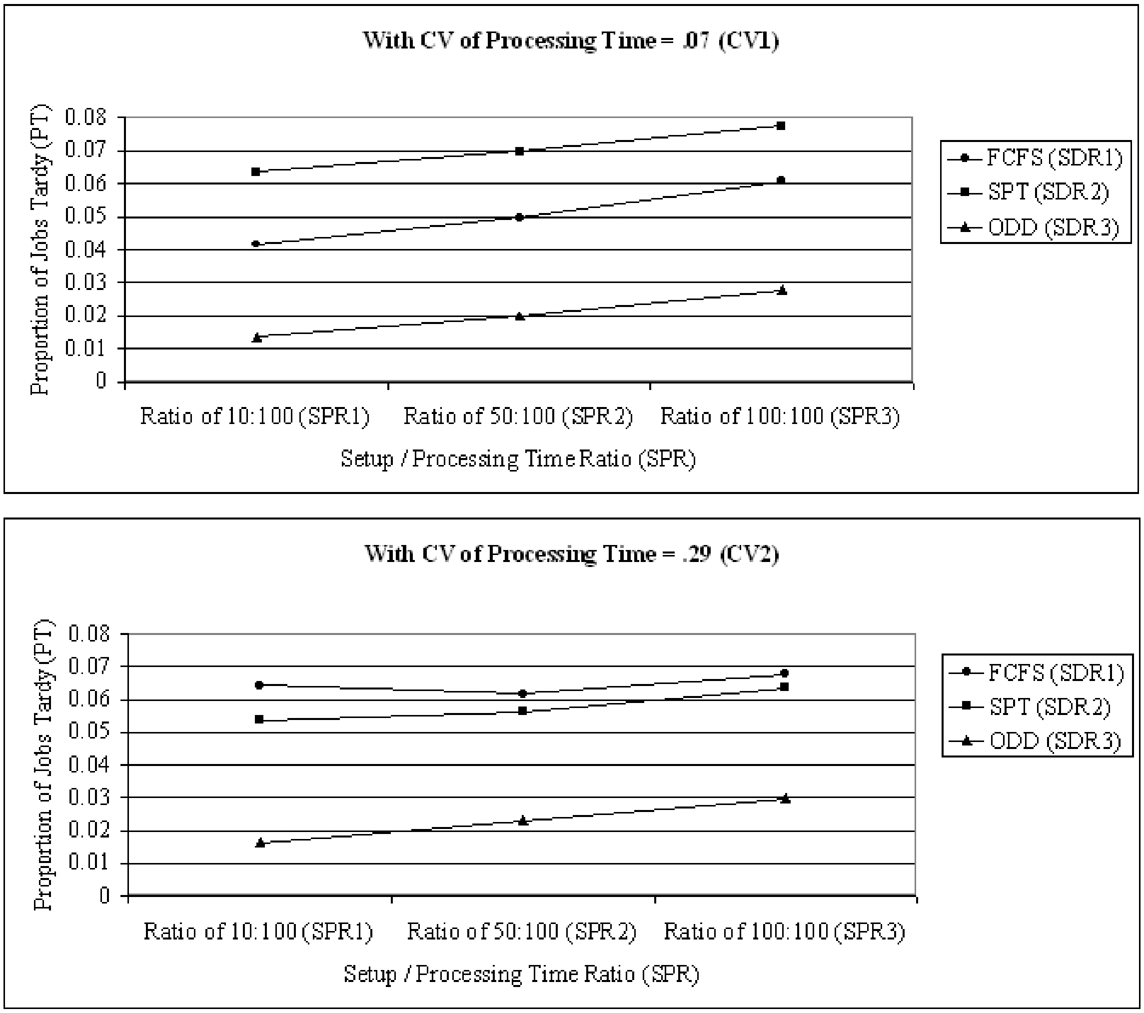
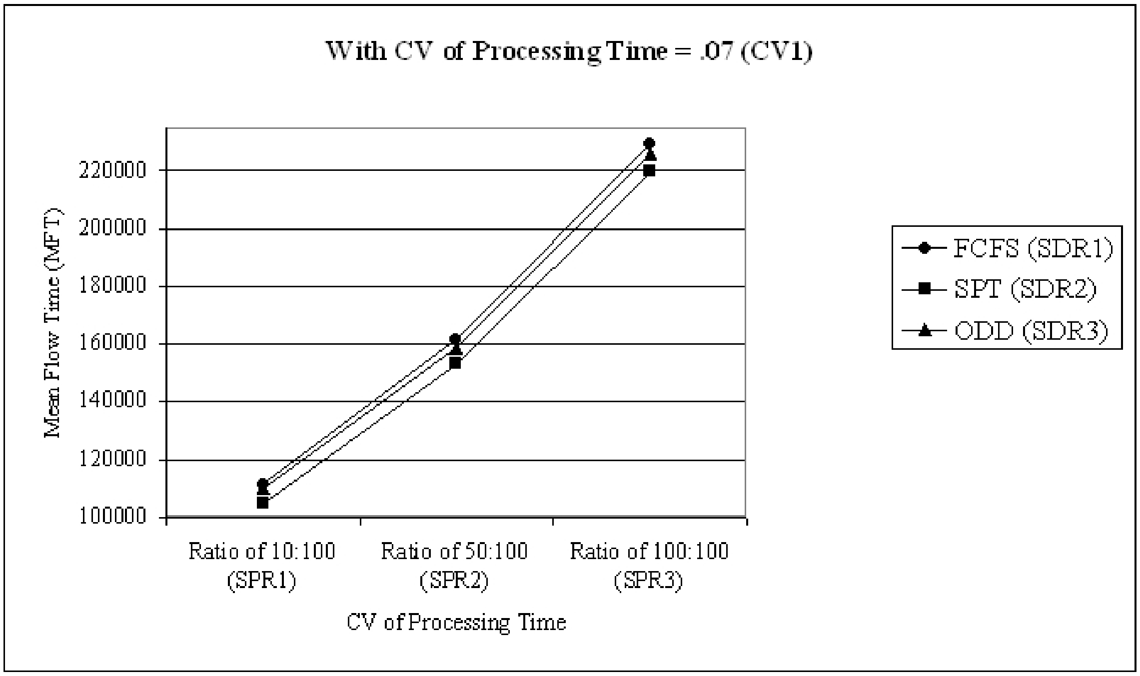


Figure 51. Proportion Tardy (PT) for Setup/Processing Time Ratio (SPR), Secondary Dispatching Rule (SDR), and CV of Processing Time (CV) with Loose Due Dates (K2)



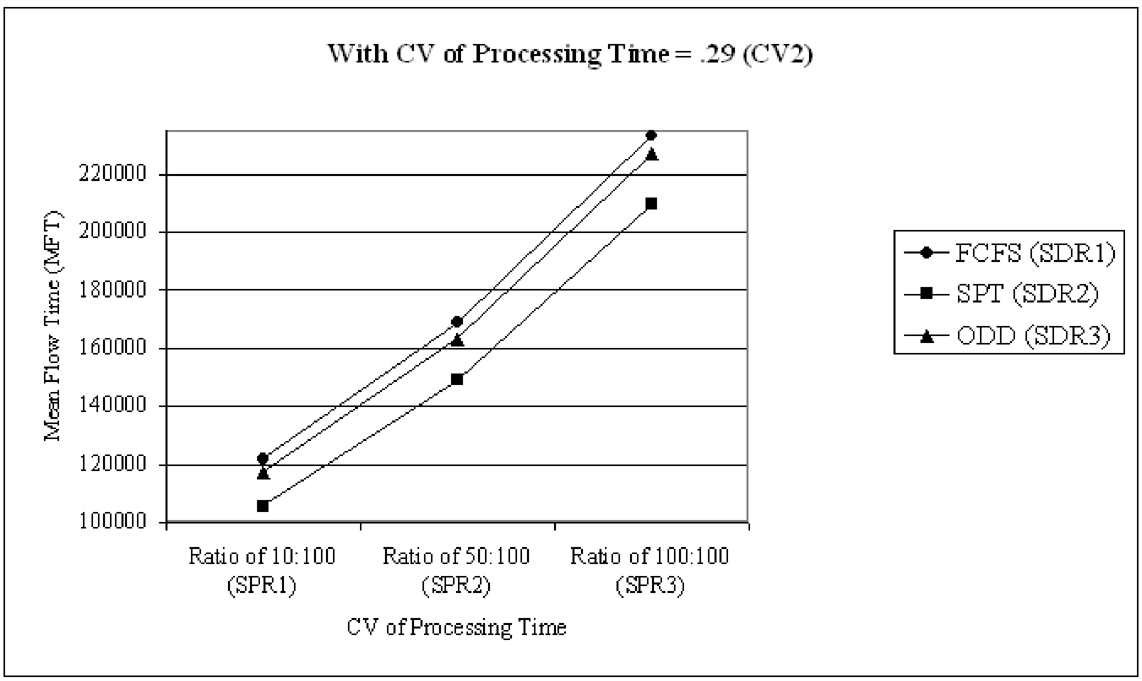


Figure 52. Mean Flow Time (MFT) for Setup/Processing Time Ratio (SPR), Secondary Dispatching Rule (SDR), and CV of Processing Time (CV) with Loose Due Dates (K2)

Again, it should be stressed that the conclusions for this hypothesis hold regardless of whether RFID or bar coding is used. For example, even though Figure 51 and Figure 52 were produced with aggregates of the tracking methods (i.e., the average of TM1-TM5), the conclusions are the same even when looking at plots (not shown here) that were created solely with RFID or bar coding data: the ODD dispatching rule (SDR3) offers less of a trade-off in mean flow time (MFT) versus proportion tardy (PT) performance compared to the shortest processing time (SPT) dispatching rule (SDR2), and ODD is always superior to the first come, first served (FCFS) dispatching rule (SDR1).

The **key finding related to the analysis for Hypothesis 6** can be summarized as follows:

SPT (SDR2) performs better than ODD (SDR3) for the mean flow time (MFT) criterion when realistic due dates (K2) are used (at $p<.001$ at CV1 and CV2 for SPR1 and SPR2, at $p<.01$ at CV1 for SPR3, and at $p<.001$ for CV2 at SPR3). In contrast, ODD is always better ($p<.001$) than the SPT dispatching rule for the proportion tardy (PT) metric, regardless of CV and SPR, when realistic due date setting (K2) is used. The trade-off can be put in perspective by considering that the SPT rule results in PT that is 2-3 *times* as large as when ODD is used, whereas the MFT for ODD is only approximately 3-5 *percent* more than with the SPT rule with low CV (CV1), and approximately 8-11 *percent* more with high CV (CV2). *The operating policies used (e.g., secondary dispatching rules) significantly affect the benefits (e.g., mean flow time and proportion tardy) from RFID implementations.*

5.7 Hypothesis 7: Proportion of jobs tardy (PT) performance should be better when there is more slack allowance for due dates (K2). Stated more formally, the K2 due date multiplier factor level should result in smaller PT (statistically significant at no more than $p < .10$) compared to when the K1 factor level is used.

The ANOVA in Figure 29 suggests several interactions for proportion tardy (PT) involving due date tightness (K), but in each case, examination of the corresponding data shows that PT performance is better when there is more slack allowance (K2 compared to K1), typically at $p<.001$, which is compatible with past research and helps validate the model. Figure 53 provides an example of the interactions, for TM*NTL*K, statistically significant at $p<.001$. As demonstrated earlier, when using RFID (TM1), increased lot streaming (higher NTL) results in PT improvement, but with diminishing returns. The improvement is less when there is more slack allowance (K2). When using fast deterministic bar coding (TM2) or slow deterministic bar coding (TM3), performance first improves, and then gets worse, with increased lot streaming (higher NTL). With both TM2 and TM3, though, the effect is dampened with more slack allowance (K2). The other interactions involving K are similar; the shape might be slightly altered by the levels of K, but performance is always better with more slack allowance (K2). Thus, there is support for Hypothesis 7.

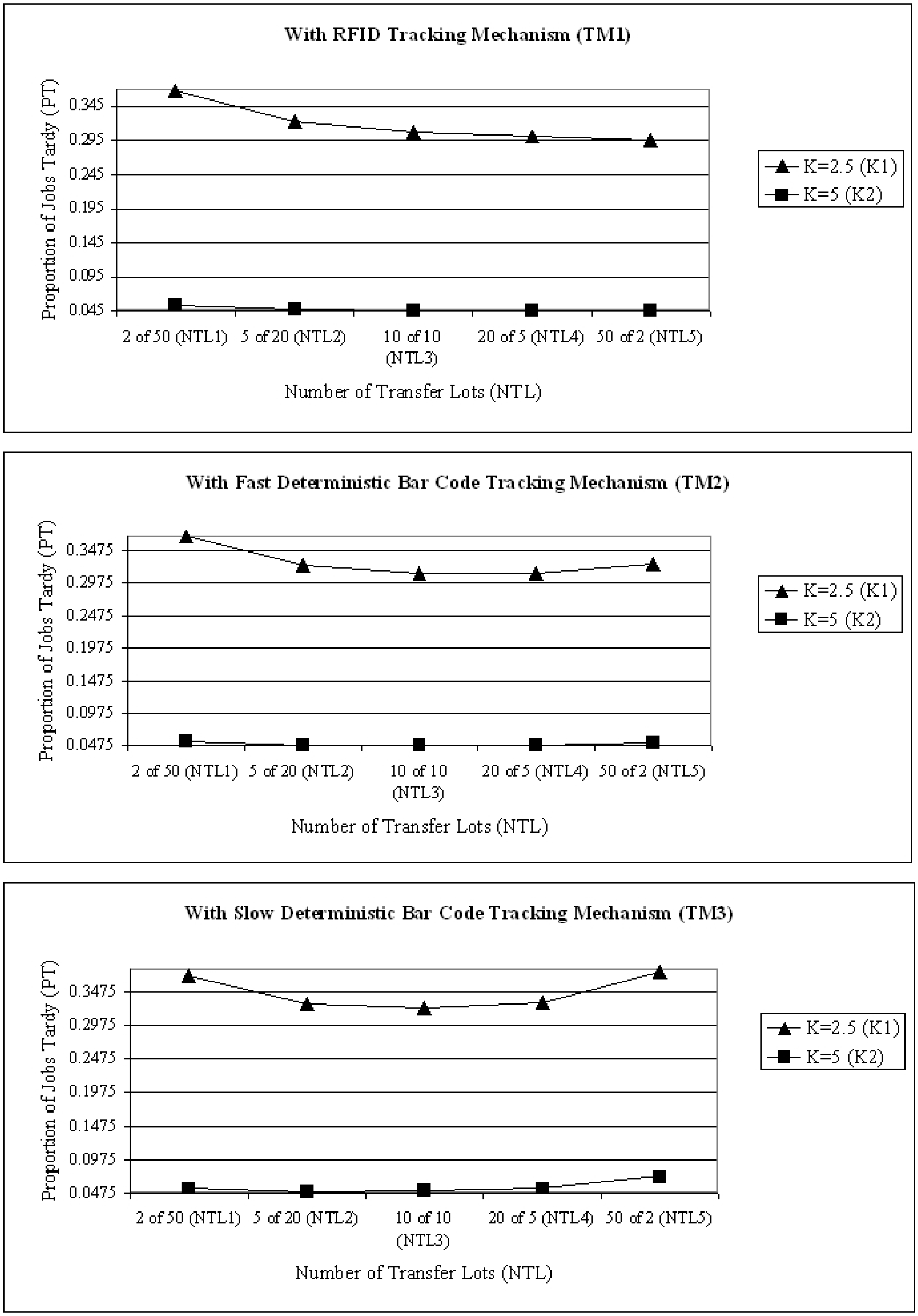


Figure 53. Proportion Tardy (PT) for Number of Transfer Lots (NTL), Due Date Tightness (K), and Tracking Mechanism (TM)

It is interesting to note that more slack (e.g., K2) not only leads to lower proportion tardy, it also acts as a dampening effect for the benefits of increased lot streaming (higher NTL), as suggested by the statistically significant ($p<.001$) NTL*K and TM*NTL*K interaction effects. For example, Figure 53 shows that when RFID (TM1) is being used, moving from NTL1 to NTL5 results in a PT reduction of 19.49 percent with tight due dates (K1), but the reduction is only 15.31 percent with loose due dates (K2). This can be explained by the fact that with less slack, there is more opportunity for the increased lot streaming to make a beneficial difference (there are more tardy jobs with tight due dates that can be improved to on-time as a result of increased lot streaming).

The **key finding related to the analysis for Hypothesis 7** can be summarized as follows:

> The ANOVA for proportion tardy (PT) in Figure 29 suggests several interactions involving due date tightness (K), but in each case, examination of the corresponding data shows that PT performance is better when there is more slack allowance (K2 compared to K1), typically at $p<.001$. Examination of the data behind the statistically significant ($p<.001$) interaction effects for extent of lot streaming and due date tightness (NTL*K) and tracking method, extent of lot streaming, and due date tightness (TM*NTL*K) show that more slack (e.g., K2) not only leads to lower proportion tardy, it also acts as a dampening effect for the benefits of increased lot streaming (higher NTL) when using RFID (TM1). *The operating policies used (e.g., due date tightness) significantly affect the benefit*

(e.g., proportion tardy) from the use of RFID and associated process changes (e.g., increased lot streaming as represented by higher NTL).

CHAPTER 6

CONCLUSION

This dissertation has examined how radio frequency identification (RFID) can be used to enable improved manufacturing performance. As noted by Woods (2004) and Swedberg (2006), this technology can change the economics of many processes that were previously not feasible. Typically this is because RFID's sensing capability means that bar codes do not need to be manual positioned, and so material can be instantaneously and automatically tracked from relatively far away. This better data collection means that the labor associated with counting and tracing can often be eliminated. The research for this dissertation shows how RFID can enable the use of smaller lot sizes than were previously possible because of RFID's ability to quickly and automatically track material while meeting demanding control and traceability requirements. Such RFID capabilities lead to improved flow time and tardiness performance compared to data collection alternatives such as bar coding.

Under several conditions and policies, the research quantitatively compared RFID technology versus bar coding and examined performance trade-offs associated with different sizes of production lots. The experimental design considered factors of the amount of time it takes to identify a transfer lot, process reliability (read batching), the number of transfer lots, the setup/processing time ratio, the type of dispatching rule used, the amount of variation between processing times, and the amount of due date slack. The performance trade-off involves improved flow times and tardiness versus increased material movements. By building on classic manufacturing planning and control literature, the dissertation developed generalizable strategic and tactical insights about the applicability of an increasingly "hot" technology, RFID, in manufacturing. The below summaries correspond to the key results from each hypothesis. Each summary includes one or more italicized managerial "take-aways".

6.1 Hypothesis 1 and associated analysis

Hypothesis 1: The forms of bar coding with stochastic read times should show worse mean flow time (MFT) and proportion tardy (PT) performance than their deterministic bar coding counterparts. Stated more formally, TM4 should have numerically higher MFT and PT than TM2, and TM5 should have numerically higher MFT and PT than TM3, statistically significant at no more than $p<.10$ when performing pairwise comparisons.

Previous shop floor production and material flow research had not included bar code read times, much less differentiated between potential differences in deterministic versus stochastic read times. Statistical tests revealed that the performance differences for mean flow time (MFT) and proportion of jobs tardy (PT) between the deterministic and stochastic levels of fast and slow bar coding (TM2 versus TM4, and TM3 versus

TM5) were not statistically significant at $p < .10$, and therefore there is no support for Hypothesis 1. Figure 31 and Figure 32 illustrate that stochastic bar coding read times (TM4 and TM5) are unlikely to lead to significantly different results compared to deterministic read times (TM2 and TM3). The hypothesis was originally motivated by basic queuing and "factory physics" principles discussed in Hopp and Spearman (2001), that increasing variability degrades the performance of a manufacturing system. Lee and Whang (2005) noted that the cornerstone of Motorola's widely acclaimed Six Sigma program was to continuously reduce process variability, so a reduction in bar code read time variability could reasonably be expected to lead to improved MFT and PT performance. A gamma distribution was used to obtain a long "tail" of statistical variance, but it is possible that if a different distribution with even more variability was used, then there would have been a significant difference between deterministic and stochastic read times. The absence of statistically significant results for Hypothesis 1 is likely because the variability of bar code read times is small relative to the total processing time of parts, both as modeled and in the real world. *Because these results indicate there is no difference in mean flow time and proportion tardy based on the use of deterministic versus stochastic bar coding read times, future research can use deterministic times and therefore use more parsimonious models or have additional space in the experimental design to incorporate additional factors that lead to more realistic modeling of RFID technology, bar coding, and the manufacturing process. This is particularly important for researchers who struggle to include additional factors that* *make their models more realistic without introducing unnecessary complexity*. See section 5.1 for more information.

6.2 Hypothesis 2 and associated analysis

Hypothesis 2: With increased transfer lots (NTL), mean flow time (MFT) and proportion of jobs tardy (PT) will improve when using RFID (with TM1). Stated more formally, with the tracking mechanism held constant at level TM1, increasing NTL should result in increasingly smaller MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels. When *not* using RFID (when not using TM1), increased NTL will result in better MFT and PT performance at first, and then lead to worse performance. Stated more formally, when using TM2 - TM5, increasing NTL should result in increasingly smaller MFT and PT up to some switchover point, before further increasing NTL results in increasingly larger MFT and PT, statistically significant at no more than $p<.10$ when performing pairwise comparisons between adjacent NTL levels.

There were statistically significant differences ($p<.01$) in mean flow time (MFT) and proportion tardy (PT) between adjacent lot streaming (NTL) levels when holding the tracking mechanism (TM) constant. The time spent performing the bar code tracking activity (TM2-TM5) eventually outweighs the performance gains from increasing the number of transfer lots (NTL), and thus generates U-shaped curves in Figure 31 and Figure 32 for the fast (TM2 and TM4) and slow (TM3 and TM5) bar coding tracking activities. These results support Hypothesis 2. Previous research had not considered the time needed for the data collection activity, but this dissertation has demonstrated that different conclusions are reached when including the data collection portion of the process (e.g., use of smaller production lots can actually result in worse performance when bar coding is used). Because of the need to compare RFID technology (TM1) against existing data collection alternatives, this result is important regardless of whether RFID or bar coding (TM2-TM5) is being modeled. *This research illustrates the benefit of incorporating the attributes of the data collection method (e.g., the time to read an RFID tag or bar code label) in models in order to develop accurate conclusions about production processes.*

When there are only 2 transfer lots of 50 units each (NTL1), the difference between RFID (TM1) versus fast (TM2 or TM4) and slow (TM3 or TM5) bar coding is statistically significant for mean flow time ($p<.05$ and $p<.001$, respectively) and proportion tardy ($p<.10$ and $p<.001$, respectively). Even though there was statistical significance, there was less than 1 percent difference in mean flow time (MFT) and proportion tardy (PT) performance between RFID and bar coding (see Figure 31 and Figure 32). *Given the higher cost of RFID technology, it may make more sense to use bar coding if the process is not enhanced (e.g., if increased lot streaming such as NTL4 or NTL5 is not used) to take advantage of RFID's key enabling features such as better traceability*. This is compatible with the analysis and reporting of Byrnes (2004), Ericson (2004c), and Sliwa (2005b), who all stressed the importance of making process changes in conjunction with RFID use.

When using 5 transfer lots or more (NTL2-NTL5), the differences between RFID (TM1) and fast (TM2 and TM4) and slow (TM3 and TM5) bar coding become more statistically significant ($p<.001$ for all MFT and PT comparisons between NTL2 and NTL5, as opposed to some comparisons that were only $p<.10$ or $p<.05$ for NTL1). The rise in statistically significant differences between RFID (TM1) and bar coding (TM2-TM5) with increased lot streaming (higher NTL) parallels an increase in practically significant differences, allowing improvement of over 5 percent when RFID is used, as seen Figure 31 and Figure 32. *These results show that if RFID technology is used to enable substantially changed processes (e.g., because its better traceability facilitates increased lot streaming, as represented by NTL3-NTL5), it can lead to much better performance (e.g., mean flow time and proportion tardy) than bar coding.* This is compatible with the findings of Hardgrave et al. (2005), who described how RFID can enable changed processes in the retail environment to significantly reduce out of stock inventory.

As noted earlier, the improvement in mean flow time (MFT) and proportion tardy (PT) performance between adjacent lot streaming (NTL) levels is statistically significant at $p<.001$ when RFID (TM1) is used. From a practical perspective, though, the percent reduction in mean flow time (MFT) when moving from 20 transfer lots of size 5 (NTL4) to 50 transfer lots of size 2 (NTL5) is only .8 percent, and the reduction in proportion tardy (PT) is only 1.4 percent. In contrast, the reduction in MFT when moving from 2 transfer lots of size 50 (NTL1) to 5 transfer lots of size 20 (NTL2) is 2.6 percent, and the reduction in PT is 12.1 percent. As can be seen in Figure 31 and Figure 32, there are diminishing returns in MFT and PT performance improvements with increased use of lot streaming (higher NTL) when RFID is used. This is compatible with previous lot streaming research that found diminishing returns with increasingly smaller transfer lots (Smunt et al., 1996; Biskup and Feldmann, 2006). *Even though RFID technology can enable valuable process changes for manufacturers (e.g., increased use of lot streaming as a result of better traceability compared to bar coding), those process changes may offer diminishing returns (e.g., ever smaller reductions in mean flow time and proportion tardy) when carried to extremes (e.g., splitting a job of 100 units into 50 transfer lots).*

See section 5.2 for more information.

6.3 Hypothesis 3 and associated analysis

Hypothesis 3: The improvement in mean flow time (MFT) and proportion of jobs tardy (PT) performance with increased lot streaming (higher NTL) should be lower when the setup / processing time ratio increases (when SPR increases). Stated more formally, an NTL*SPR interaction effect (statistically significant at no more than $p<.10$) is expected to be identified for MFT and PT.

There is an interaction effect between the number of transfer lots used (NTL) and the setup/processing time ratio (SPR), statistically significant at $p<.05$ for mean flow time (MFT), and at $p<.001$ for proportion tardy (PT). As can be seen in Figure 33 and Figure 34, the percent reductions in MFT and PT are greatest when the setup/processing time ratio is low (e.g., the 10:100 ratio of SPR1). This supports Hypothesis 3 and is compatible with the findings of Smunt et al. (1996). *The use of smaller lot sizes enabled* *by RFID drives reductions in mean flow time and proportion tardy, and those reductions are sensitive to the operating conditions (e.g., the setup/processing time ratio).*

See section 5.3 for more information.

6.4 Hypothesis 4 and associated analysis

Hypothesis 4: With the tracking mechanism held constant at RFID (TM1), increasing the amount of lot streaming (NTL) should result in increasingly numerous material movements (MM), statistically significant at no more than $p < .10$ when performing pairwise comparisons between adjacent NTL levels.

Post-hoc tests motivated by the ANOVA in Figure 30 indicate statistically significant increases ($p<.001$) in the total number of material movements (MM) between adjacent lot streaming (NTL) levels when using RFID (TM1). The plot in Figure 35 provides visual support of the magnitude of the increase in material movements, also supporting Hypothesis 4. This is compatible with the findings of Kher et al. (2000), who also found significant increases in material movements when smaller transfer lots were used, but they examined a flow shop (and not a job shop as in this research), and they modeled pull material movements slightly differently (see Chapter 3 for more information). Figure 36 shows that the diminishing returns in mean flow time (MFT) and proportion of jobs tardy (PT) improvement from increased lot streaming (higher NTL) must be traded-off against the relatively sharper increase in material movements (MM). *As with other technology investments and process changes, RFID and the move to incorporate reduced lot sizes (higher NTL) sometimes involve trade-offs (e.g., reduced* *flow times and proportion tardy are obtained at the expense of increased material movements between work centers).* See section 5.4 for more information.

The ANOVA in Figure 30 (as well as a follow-up ANOVA using just the RFID treatments) indicate an interaction between the extent of lot streaming, setup/processing time ratio, and CV of processing time (NTL*SPR*CV) for the number of material movements (MM), $p<.001$. Figure 37 shows that the increase in MM with more lot streaming (higher NTL) is larger when the SPR ratio is lower (e.g., the increase in MM is larger with SPR1 compared to SPR3). Also related to the NTL*SPR*CV interaction, the advantages of RFID with increased lot streaming will be greater when the CV of the processing times between work centers is low (compare the top and bottom portions of Figure 37), so there are advantages in trying to group work centers and material flow to minimize large differences in processing times. When the SPR ratio is low (e.g., SPR1), and especially when the CV of processing times is also large (such as represented by CV2), extreme levels of lot streaming (e.g., NTL5) may not be appropriate, even when automation and RFID is used. Extreme levels of lot streaming may be inappropriate because of the massive increase in material movements (e.g., the move from NTL4 to NTL5 results in a 46.7 percent increase under those conditions, statistically significant at $p<.001$). Previous lot streaming research had not considered the impact of smaller transfer lots on material movements in a job shop, much less potential interaction effects from operating conditions such as setup/processing time ratios. Although Kher et al. (2000) had also found that the increase in material movements when using smaller transfer lots is greater when the setup/processing time ratio is relatively low, their research was in the context of a flow shop, not a job shop, they had not considered multiple factor levels for the CV of processing time, and they modeled pull material movements slightly differently (see Chapter 3 for more information). See section 5.4.1 for more information about the relationship between the operating conditions and the increase in material movements with smaller transfer lots (more lot streaming).

The increase in the number of material movements associated with RFID and increased lot streaming (higher NTL) is sensitive to the operating conditions (e.g., the setup/processing time ratio and the CV of processing time between work centers). Managers should realize that with moderate and high SPR ratios (e.g., SPR2 and SPR3), investments in automated material handling might be necessary when using high levels of lot streaming, even when also employing RFID technology. When the SPR ratio is low (e.g., SPR1), the increase in material movements with even moderate levels of lot streaming (e.g., NTL2) might be too much even if automated handling is used, thus allowing only minimal levels of lot streaming (e.g., NTL1) to be used.

Stated another way, to accomplish the full benefit of RFID without incurring trade-off performance penalties that negate those benefits, manufacturers may need to invest in automated material handling equipment. Advanced automation is a reality today, and companies that are adept at using RFID could also plausibly be expected to be skilled at using other forms of shop floor automation. Hall (2006) describes how Matsushita replaced their conveyor system with clusters of robots that are coordinated and synchronized with each other so as to enable fast, smooth, and efficient production. The visibility from RFID could be integrated with such a system to further choreograph the movement of material. For example, Brusey et al. (2003) describe how RFID can be used with intelligent robotic systems to support improved material handling. Garcia et al. (2003) note that because bar codes need to be positioned with the label facing readers, conveyors and other transfer systems experience problems that make bar codes unreliable for automated material handling. Thus, besides the improved traceability offered by RFID that was described in Chapter 3, RFID enables the automated material handling that is vital for achieving performance improvements with smaller lot sizes.

The material movements (MM) ANOVA for the full experimental design (Figure 30) indicate an interaction involving the extent of lot streaming, choice of secondary dispatching rule, and CV of processing time (NTL*SDR*CV), statistically significant at $p<.001$. A follow-up MM ANOVA using only the RFID (TM1) treatments came to the same conclusion. Figure 38 shows that at each of the NTL levels, the FCFS rule (SDR1) is best (has the lowest MM value), followed by ODD (SDR3) and SPT (SDR2), statistically significant at $p<.001$. Figure 38 also illustrates that the difference in MM between each of the dispatching rules grows between NTL1 and NTL5, statistically significant at $p<.001$. Previous lot streaming research had not considered the impact of smaller transfer lots on material movements in a job shop, much less potential interaction effects from operating policies such as secondary dispatching rules. Although Kher et al. (2000) had also found that smaller transfer lots increase material movements in a flow shop, they had not considered interaction effects from secondary dispatching rules, and they modeled pull material movements slightly differently (see Chapter 3 for more information). *The increase in the number of material movements is sensitive to the* *interaction of the operating policies used (e.g., the secondary dispatching rule) and process changes that might be made as a result of RFID's enabling characteristics (e.g., more lot streaming made possible by the technology's enhanced traceability).* See section 5.4.2 for more information.

The improvement in mean flow time (MFT) and proportion tardy (PT) for medium (SPR2) and high (SPR3) setup/processing time ratios when moving from the NTL4 to NTL5 level of lot streaming is statistically significant at no more than $p<.01$. For both SPR1 and SPR2, the *raw* MFT, PT, and material movement (MM) values (not comparing to NTL baselines and converted to percentages) are statistically higher ($p<.001$) at CV2 compared to the corresponding values at CV1 (note that higher *raw* MFT, PT, and MM values are worse). Although the tradeoff of increased material movements (MM) when moving from NTL4 to NTL5 is statistically significant at $p<.001$ for each of SPR1 - SPR3, when the CV is low (e.g., CV1), the percentage increase when moving from the NTL1 baseline to NTL5 is 251.0 percent with SPR1, the increase from the NTL1 baseline of SPR2 is only 38.9 percent, and the increase from the NTL1 baseline of SPR1 is only 13.6 percent. Previous lot streaming research had not considered the material movement tradeoff in a job shop, much less potential interaction effects from operating conditions and policies. Kher et al. (2000) had also considered the increase in material movements in a flow shop, but they did not explicitly contrast the tradeoffs for different scenarios, and they modeled pull material movements slightly differently (see Chapter 3 for more information). *The trade-offs associated with RFID technology and related process changes (e.g., improvements in mean flow time and* *proportion tardy versus increases in the number of material movements as a result of increased lot streaming enabled by RFID's traceability) are sensitive to the operating conditions (e.g., the setup/processing time ratio and CV of processing time).* See section 5.4.3 for more information.

At a moderate level of lot streaming (NTL3), the difference between RFID (TM1) and slow deterministic bar coding (TM3) is statistically significant at $p<.001$ for mean flow time (MFT), and at $p<.01$ for proportion tardy (PT), when there is a high setup/processing ratio (SPR3), low CV of processing time (CV1), loose due dates (K2), and the ODD dispatching rule is used (SDR3). The difference between RFID and bar coding grows even more significant with increased lot streaming (higher NTL). When comparing RFID against fast deterministic bar coding (TM2) when there is a high setup/processing ratio (SPR3) and the conditions are otherwise the same, the best MFT performance for RFID is statistically better at $p<.01$ for mean flow time (MFT) compared to the best bar coding performance, but the best PT performance for each (bar coding and RFID) are not statistically significant at $p<.10$. When conditions are the same as the previous examples, except with a moderate setup/processing time ratio (SPR2), RFID PT performance compared to fast bar coding (TM2) is better even at low and moderate levels of lot streaming (significant at $p<.05$ for NTL2 and $p<.01$ for NTL3). MFT performance with RFID is at least as good as bar coding performance; at NTL3, the difference is statistically significant at $p<.001$, and as with PT, the gap grows larger with higher levels of lot streaming (increased NTL). In all three of the aforementioned scenarios (TM1 versus TM3 at SPR3, TM1 versus TM2 at SPR3, and TM1 versus TM2 at SPR2), the difference in material movements between RFID and bar coding is either not statistically significant at p<.10, or is not practically very large (e.g., less than 1.2 percent). Previous research that quantitatively compares RFID and bar coding in the context of a job shop does not exist. The closest analysis was by Gaukler and Hausman (under review), who compared the savings of RFID over bar coding in the context of an assembly line.

The "takeaway" for managers is that RFID technology and increased lot streaming might be most appropriate:

- *when setup times are moderate (e.g., SPR2), regardless of whether the data collection alternative (e.g., bar coding) is relatively fast or slow,*
- *or when setup times are high (e.g., SPR3) and the data collection alternative is relatively slow.*

The analysis for section 5.4.4 showed that material movements can increase by over 200 percent when setup times are low (e.g., SPR1) and the extent of lot streaming is increased from low (e.g., NTL1) to high (e.g., NTL5). Such increases in material movements will not be feasible for many companies, even if high levels of automated material handling are used. Together with the analysis for Hypothesis 2, which showed that RFID and bar coding have nearly identical performance when low levels of lot streaming are used (which is necessary to avoid excessive material movements with low SPR ratios), the combined results show that it will often not make sense to use RFID technology when the SPR ratio is low (e.g., SPR1), because bar coding can offer nearly the same performance, at presumably less cost. Stated another way, even when RFID results in overall *improved performance without much of a tradeoff in increased material movements, an alternative such as fast bar coding might still be competitive in some situations.*

6.5 Hypothesis 5 and associated analysis

Hypothesis 5: Mean flow time (MFT) and proportion of jobs tardy (PT) should increase (be worse) with more read batching (with greater RB). Stated more formally, increasing levels of RB should result in higher MFT and PT, statistically significant at no more than $p < .10$.

This hypothesis and associated analysis looked at how batching the reads of transfer lots affected the various dependent variables because of the disrupted pull material flow. Read batching can be interpreted as a lack of data collection process conformance by workers who incorrectly do not read the bar code label after completion of each transfer lot, or it can be interpreted as the RFID system having less than perfect read reliability after completion of each transfer lot. The previous research that came closest to examining this issue was by Gaukler and Hausman (under review), who considered improvements in process conformance by using RFID instead of bar coding. They created a model in the context of an assembly line where the RFID system could be used to more quickly and reliably verify parts that might otherwise be incorrectly used during the assembly process, thus showing how RFID could help prevent quality problems.

Tests for MFT indicate that the difference between RB1 and RB2 is significant ($p<.05$), between RB1 and RB3 is significant (p.<001), and between RB2 and RB3 is significant ($p<.01$). Post-hoc tests for PT indicate that the difference between RB1 and RB2 is not significant ($p>.10$), between RB1 and RB3 is significant ($p.<001$), and between RB2 and RB3 is significant ($p<.05$). Examining tables and Figure 44 and Figure 45 shows that even though there are statistical significant differences between the RB levels (thus supporting Hypothesis 5), the largest difference in the dependent variable is less than one percent.

When comparing RFID (TM1) with high read batching (RB3) versus fast bar coding (TM2) with no read batching (RB1) under the conditions shown in Figure 46, RFID has significantly better MFT than fast bar coding, $p<.01$, and also significantly better PT, $p<.10$, and the gap grows wider with increased lot streaming (higher NTL). Figure 46 illustrates that even if RFID read reliability is lower than bar coding (e.g., as modeled by the higher RB3 read batching factor level for RFID compared to the RB1 level for bar coding), RFID (TM1) can still provide superior mean flow time (MFT) and proportion of jobs tardy (PT) performance compared to bar coding (whether TM2 or TM3). *Even if the relative newness of RFID leads to lower read reliability (e.g., RB3) compared to bar coding because of technology issues that are yet to be resolved, RFID can still be a viable candidate for consideration in process improvement projects (e.g., to enable increased lot streaming that will lead to reduced flow times and proportion tardy).* See section 5.5 for more information.

6.6 Hypothesis 6 and associated analysis

Hypothesis 6: Mean flow time (MFT) should be best with the shortest processing (SPT) dispatching rule (SDR2). When due dates are tight (K1), then proportion of jobs tardy (PT) should be best for the SPT dispatching rule (SDR2). When due dates are loose (K2), then PT should be best for the earliest operation due date (ODD) dispatching rule (SDR3). Stated more formally, the SPT rule (SDR2) is expected to be statistically better (at no more than $p<.10$) than FCFS (SDR1) and ODD (SDR3) for MFT. An SDR*K interaction effect is expected to be identified for the proportion of jobs tardy (PT), with the SPT rule (SDR2) being statistically better (at no more than $p<.10$) with tight due dates (K1), and the ODD rule (SDR3) being statistically better (at no more than $p<.10$) for loose due dates (K2).

The ANOVA in Figure 28 indicates there are several significant SDR interactions for MFT, including SDR*K ($p<.001$). Pairwise comparisons of the data used to make Figure 48 indicate that the difference between SPT and ODD is significant at $p<.001$ at both K1 and K2. The ANOVA in Figure 29 indicates there are several significant SDR interactions for PT, including SDR*K and SDR*CV*K ($p<.001$ for each). Figure 49 shows that when due dates are tight (K1), the SPT rule is best ($p<0.01$ when compared against ODD with pairwise tests for both CV1 and CV2), and that when due dates are loose (K2), the ODD rule is best for minimizing the proportion tardy ($p<.001$ when compared against FCFS for CV1 and $p<.001$ when compared against SPT for CV2). These MFT and PT results are both congruent with Hypothesis 6 and are compatible with the theory developed in earlier research (Baker, 1984; Jayamohan and Chandrasekharan, 2000).

Given that SPT is always best for MFT performance, but is sometimes inferior to other secondary dispatching rules for PT performance when considering a range of factor levels from the literature, one might wonder how to balance the trade-off. SPT (SDR2) performs better than ODD (SDR3) for the mean flow time (MFT) criterion when realistic due dates (K2) are used (at $p<.001$ at CV1 and CV2 for SPR1 and SPR2, at $p<.01$ at CV1 for SPR3, and at $p<.001$ for CV2 at SPR3). In contrast, ODD is always better ($p<.001$) than the SPT dispatching rule for the proportion tardy (PT) metric, regardless of CV and SPR, when realistic due date setting (e.g., K2) is used. The trade-off can be put in perspective by considering that the SPT rule results in PT that is 2-3 *times* as large as when ODD is used, whereas the MFT for ODD is only approximately 3-5 *percent* more than with the SPT rule with low CV (CV1), and approximately 8-11 *percent* more with high CV (CV2). *The operating policies used (e.g., secondary dispatching rules) significantly affect the benefits (e.g., mean flow time and proportion tardy) from RFID implementations.*

6.7 Hypothesis 7 and associated analysis

Hypothesis 7: Proportion of jobs tardy (PT) performance should be better when there is more slack allowance for due dates (K2). Stated more formally, the K2 due date multiplier factor level should result in smaller PT (statistically significant at no more than $p < .10$) compared to when the K1 factor level is used.

The ANOVA in Figure 29 suggests several interactions for proportion tardy (PT) involving due date tightness (K), but in each case, examination of the corresponding data shows that PT performance is better when there is more slack allowance (K2 compared to K1), typically at $p<.001$. These results support Hypothesis 7 and are compatible with the findings of Baker and Kanet (1983), who examined the impact of different due date tightness levels on proportion tardy in a job shop but did not consider lot streaming, and with Wagner and Ragatz (1994), who examined mean tardiness (but not proportion tardy) in the context of a job shop using lot streaming.

Examination of the data behind the statistically significant ($p<.001$) interaction effects for tracking method, extent of lot streaming, and due date tightness (TM*NTL*K) show that more slack (e.g., K2 compared to K1) not only leads to lower proportion tardy, it also acts as a dampening effect for the benefits of increased lot streaming (higher NTL) when using RFID (TM1). *The operating policies used (e.g., due date tightness) significantly affect the benefit (e.g., proportion tardy) from the use of RFID technology and associated process changes (e.g., increased lot streaming as represented by higher NTL).*

See 5.7 for more information.

6.8 Analysis of the relation between material handling, mix (product variety), and volume flexibility and lean production enabled by RFID

It is interesting to consider the relationship between material handling, mix (product variety), and volume flexibility and lean production enabled by RFID technology. Gerwin (1993) describes mix flexibility as supporting a number of broad product lines and/or numerous variations within a line. In contrast, volume flexibility permits increases in the timing and quantity of aggregate production levels (Gerwin, 1993). Ittner and MacDuffie (1995) observed that with increasing part, option, and product mix complexity comes greater material handling and control requirements. Zhang, Vonderembse, and Lim (2003) empirically demonstrated that volume and mix flexibilities cannot be achieved directly; they are attained through the implementation of flexibility manufacturing competencies, including material handling flexibility.

This section will argue that RFID technology enables efficient (lean) production of a broad product mix in varying volumes, but an investment in material handling flexibility (automated material handling) is also required. RFID and automated material handling can help enable a move off of the traditional Hayes-Wheelwright product/process matrix, which has historically suggested that efficient production requires focus that allows relatively little variety (Hayes and Wheelwright, 1979; Heim, 2006). In essence, RFID and automated material handling enable mass customization (Brusey et al., 2003; Fleisch, Ringbeck, Stroh, Plenge, and Strassner, 2004; Gunasekaran and Ngai, 2005; Schmitt, Michahelles, and Fleisch, 2006). Gunasekaran and Ngai (2005) stated that RFID "provides major improvements to the efficiency and accuracy of materials handling systems” and enables easy and effective tracking of materials though build-to-order supply chains that require mix and volume flexibility. Real-time systems (such those made possible by RFID) are becoming increasingly important because of the move from make-to-stock (MTS) to make-to-order (MTO) systems that need real-time visibility of inventory in order to quickly supply the mix variety demanded by customers (Scott, 2005; Trebilcock, 2005).

Given the increased visibility, control, and productivity associated with RFID, it is not surprising that the trend toward lean manufacturing is called one of the top drivers of RFID use in the automotive, aerospace, and industrial manufacturing sectors (Bacheldor, 2006a). RFID technology not only supports faster throughput (Forger, 2005; Bacheldor, 2006c), but RFID’s improved control also reduces the risk of inventory inaccuracies, misplaced resources, and other disruptions that are particularly damaging in lean environments (Ericson, 2004a; McIntyre, 2006; Tellkamp, 2006; WinWare, 2006). Nissan plans to use RFID to guide material handlers in support of just-in-time (JIT) sequencing of parts, thus reducing inventory while supporting a more complex production process than would be feasible with a less technologically advanced solution (Alper, 2006). Total Interior Systems-America uses RFID to streamline manufacturing and provide traceability for their JIT sequencing system that they use to supply seats to Toyota (Control Engineering, 2005).

Gunasekaran and Ngai (2005) noted that lean production and the principles of flexible build-to-order supply chains have historically been at odds with each other. The former has traditionally been associated with efficiencies linked to stable schedules, whereas the latter is about responsiveness built on the ability to manage unstable schedules. This dissertation has demonstrated how RFID technology can help achieve the best of both worlds, efficient lean production along with mix and volume flexibility. Job shops are associated with mix flexibility, but they are typically associated with low production volumes and relatively long lead times. By using increased lot streaming that is made possible (in part) by RFID, improved utilization and faster throughput (that enables volume flexibility) and reduced tardiness are attained that are normally associated with lean material layouts organized around linear flows that support less mix flexibility. RFID tracking also facilitates even greater product mix than what would otherwise be possible in a job shop, because the enhanced control makes it less likely that resources will be lost or inefficiently used due to the higher high variety and complexity. Thus, this dissertation quantitatively builds on the conceptual work of Kärkkäinen and Holmström (2002), who suggested that RFID technology could enable efficient customization in which products are efficiently processed and handled in small batches.

To achieve the aforementioned benefits of enhanced volume and mix flexibility in a lean manner, not only is high-speed RFID necessary, but so is effective, low variable cost material handling to support the increased material movements that result from the use of smaller transfer lots. Lean’s emphasis on the smooth flow of small lot sizes makes it a significant driving force in the development of real-time materials handling (Forger, 2005), and RFID’s real-time automated data collection and control makes it a natural fit for supporting efficient real-time materials handling, and thus lean production (Miceli, 2005). Feare (2000) describes a manufacturer of amplifiers that tripled its build-to-order capacity by incorporating material handling that tracks WIP using RFID technology and automatically balances work loads accordingly. Despite the importance of material handling flexibility, Koste, Malhotra, and Sharma (2004) indicated that it received less attention compared to other forms of flexibility, and one leading consultancy has asserted, "Materials handling has been a stumbling block in lean (Forger, 2005)." Clearly more research is needed to enhance material handling flexibility, particularly in the era of RFID.

6.9 Research extensions

This research has made several important contributions to the RFID and manufacturing literatures. Several extensions are being planned by the dissertation author to further identify conditions and policies that affect the relative attractiveness of RFID compared to other data collection technologies. The extensions can be summarized as 1) different factory shop floor production models that incorporate new or different operating condition factors, 2) development of new shop floor operating policies that take better advantage of RFID compared to policies developed for older and less capable technologies, and 3) broadening the scope of the model to include issues related to internal planning within an organization, supply chain integration, retailer operations, and opportunities after the sale when tagged products are being used by consumers.

Figure 54 provides context for how the research performed by this dissertation fits into the aforementioned possible research streams. The figure shows numerous ways that RFID can be used to improve performance within the factory, integrating the supply chain, within retail environments, and after the sale when tagged products are being used by consumers (note that this is not intended to be a comprehensive list). As indicated by italicized entries in the leftmost column of the figure, this dissertation has shown how RFID can improve *execution performance on the factory shop floor*. Figure 54 shows that even after the work of this dissertation, some RFID research opportunities still exist within the factory, and many more exist elsewhere in the supply chain.

Research opportunities to explore additional potential improvements within the factory are discussed in section 6.9.1 and 6.9.2, whereas opportunities outside the factory (such as integrating the supply chain, improving retail performance, and improving processes post-sale) are discussed in section 6.9.3. The following discussion provides supporting citations for the various entries of the figure, but it is important to note that most of them are qualitative and/or anecdotal in nature. As noted in Chapter 1, early research has either been qualitative or not provided much supporting quantitative and operational details that would help in understanding how the results generalize (Gilmore and Fralick, 2005; Murphy-Hoye et al., 2005). Thus, a substantial academic research stream potentially exists that has the opportunity to make numerous contributions to the literature.

Factory	**Supply Chain Integration**	**Retailer**	**Consumer (After the Sale)**
1. Reduced time needed for data collection leads to lower lead times and labor requirements and better service *2. Smaller lot sizes leads to lower inventories and better service* *3. Improved traceability allows small lot sizes even with high variety and customization* *4. Using RFID on shop floors with different operating conditions and using different operating policies may affect RFID's relative attractiveness* 5. Development of new operating policies (e.g., sequencing rules) could make better use of RFID and allow it to be effectively used under a broader range of operating conditions 6. Better process conformance improves quality 7. Better understanding of production processes leads to reengineering opportunities 8. Improved information for internal planning (MPS/MRP) leads to improved service and reduced safety stock, but trade-off of replanning frequency vs. instability needs to be managed	1. Reduced time for data collection during shipping, receiving, auditing, etc. reduces labor and lead times 2. Improved visibility of products, people, and equipment leads to better planning and more effective and efficient responses 3. Better understanding of supply chain processes leads to reengineering opportunities 4. Using electronic proof of delivery (EPOD) reduces waste from dispute resolution 5. Verifying promotion conformance leads to better coordinated marketing efforts 6. Visibility of location and status of perishable and seasonal products allows better inventory control 7. More reliable identification reduces fraud and counterfeiting 8. Trade-offs (e.g., increased delivery frequencies) associated with taking advantage of RFID's better information need to be managed	1. Elimination of bar coding during checkout and inventory audits eliminates wasted labor 2. Better inventory control reduces stock-outs 3. Better tracking reduces shrinkage 4. Improved understanding of customer flows through the servicescape leads to improved service, pricing, and sales	1. Improved understanding of product use leads to design improvements 2. Identification of part content facilitates improved recycling 3. Improved identification reduces recall scope

Figure 54. Research Opportunities Related to RFID's Benefits at Different Stages of a Goods-Producing Supply Chain (Research Covered by This Dissertation Shown in Italics)

6.9.1 Different factory shop floor production models that incorporate new or different operating condition factors

This dissertation considered the impact of some operating conditions (the setup/processing time ratio and the coefficient of variation of processing time between work centers) on the relative attractiveness of RFID. In order to prevent the model from growing too complex, other operating conditions were left fixed at a single factor level. This sub-section will discuss some of those operating condition factors that could be changed in order to explore the generalizability of RFID's benefits. Thus, although entry 4 in the "Factory" column of Figure 54 is shown in italics because the dissertation has examined some operating conditions and policies, this sub-section describes additional conditions that could be studied.

Incorporating multi-level material handling factors such as the time it takes to move material between work centers and limited transporter capacity would be a valuable extension. This dissertation modeled processing times that varied from job to job, but the actual processing times always equaled the expected processing times. In environments with highly uncertain processing times, RFID could add value if it was used to communicate the progress of upstream work centers to the production and materials handling scheduling systems.

It would be worthwhile to directly compare open and closed job shops (with the former, all jobs are unique, whereas with the latter, there is a finite number of job types). Wagner and Ragatz (Wagner and Ragatz, 1994) compared open and closed shops, but they did not consider all of the other factors in this dissertation, particular related to the data collection activity (e.g., the RFID tag and bar code label read times and read batching), and they did not consider the tradeoff with increased material movements.

Bottlenecks could be introduced, rather than evenly distributing the processing load. Some researchers have asserted that shops with bottlenecks are more common than balanced shops (Salegna and Park, 1996; Lockwood, Mahmoodi, Ruben, and Mosier, 2000). One potential problem with modeling bottlenecks is choosing their timing (e.g., whether they shift) and extent (e.g., how much overloaded the work centers are) such that they are realistic and generalizable. Similar to the issue of modeling bottlenecks, differing levels of flow dominance (between a pure job shop and pure flow shop) could also be examined (Monahan and Smunt, 1999). Regardless of whether a balanced shop or shop with a bottleneck is modeled, varying levels of utilization can be modeled. For example, the timely information and better utilization from RFID technology might reasonably be expected to be more advantageous when there is very high utilization.

Although some of the issues and factor levels for this dissertation were motivated by working with a company seeking neutral advice about how to expand their RFID implementation, some of the factor levels were motivated more directly from the literature so as to protect the confidentiality of the company's private data, as well as provide a familiar generalizable baseline for other researchers. Even though it could limit generalizability, some readers might prefer to see research that more closely models *all* aspects of a specific real-life company.

6.9.2 Development of new operating policies

A key research extension that flows directly from this dissertation is to develop dispatching rules (a type of operating policy) that explicitly manage the tradeoff between improved flow time and proportion tardy versus the increase in material movements. For example, it might be possible to use low setup/processing time ratios and high levels of lot streaming if a new dispatching rule was developed to better manage the tradeoff. Companies that are sophisticated enough to use RFID technology should arguably be capable of using decision rules that are more complex than the relatively simple rules developed many decades ago (such as SPT and ODD). For example, a shifting-bottleneck procedure (Adams, Balas, and Zawack, 1988) could be adapted to take advantage of a production system with dynamic arrivals and several types of uncertainty. As noted in section 6.3.1, the modeled operating conditions could be changed to include variable processing times and capacitated material handling. Such factors would greatly extend the realism of the model, but would also require new policies to adequately consider those issues.

6.9.3 Broadening the model scope to include RFID opportunities beyond the shop floor and throughout the supply chain

Besides improving process execution on the shop floor, RFID can improve factory performance in several other ways. Gaukler and Hausman (under review) showed how RFID could significantly reduce quality costs for an assembly line that features high variety (and thus non-standard application of components to the assemblies). As components are brought within range of a vehicle, an RFID system could automatically verify that they really belong to that vehicle. The data from RFID could also help the production process be better understood as a precursor to business process reengineering (Chappell et al., 2003; Byrnes, 2004; Sliwa, 2005b; Neil, 2006). For example, the data from RFID might contradict assumptions about material flow through the system, which might show that changes to the process should be implemented. Master production scheduling (MPS) and material requirements planning (MRP) planning performance might improve as a result of the more timely and accurate information from RFID (Chappell et al., 2003; Schuster, Scharfeld, Kar, Brock, and Allen, 2004). Roberti (2006) noted that companies need to figure out how to change processes so that they can react to the timely information from RFID and move inventory appropriately. Thus, MPS and MRP replanning frequencies (which affect the time to react to timely RFID data) could be added to the dissertation model. Both classic and recent planning and control research (Sridharan and Berry, 1990; Zhao and Lee, 1993; Xie, Zhao, and Lee, 2003) have indicated that less frequent replanning will often reduce total costs and system nervousness (instability). On the other hand, given the timely information from RFID about both internal and supply chain operations, it seems intuitively desirable to quickly replan in response to updated information that is automatically and continuous collected. Because RFID technology facilitates continuous data collection, some sort of filtering will likely be necessary to determine whether replanning should result in a changed schedule that offers benefits that offset the cost of system nervousness. Identifying the filtering logic will be a key contribution for ensuring that classic planning systems are updated to take advantage of the new opportunities and tradeoffs presented by RFID.

RFID may make even greater contributions outside of the factory. The supply chain integration column of Figure 54 shows opportunities where RFID might improve coordination with both the suppliers and distributor customers of a manufacturer. Because the benefits from using RFID to integrate upstream and downstream business partners are typically helpful for both the upstream and downstream companies, separate columns for upstream suppliers and downstream distributors would often be redundant. For example, McFarlane and Sheffi (2003) describe numerous supply chain processes that take place during shipping, transportation, and receiving that could potentially benefit from RFID. Those supply chain processes are typically present in the supply chain links both before and after a manufacturer, so showing Figure 54 with separate columns for the perspective of the supplier-manufacturer link and the perspective of the manufacturer-distributor link will usually not add value.

Gillette estimated 80% or more of its benefits from RFID will come from supply chain (as opposed to internal) improvements (Murphy, 2005a). Because of the trend of competing based on cumulative supply chain capabilities, the entire Gillette supply chain will likely together benefit to some degree. Information is vital to managing individual companies. The supply chain visibility of products, people, and equipment that RFID systems can offer is even more important in supply chains for planning and executing more efficient and effective responses to the realization of uncertainties. EPCglobal (2006) describes how using RFID technology to support electronic proof of delivery

(EPOD) of goods shipped across the supply chain has already demonstrated significant benefits based on the reduction of time needed to resolve disputed deliveries. Proctor & Gamble has discussed how RFID can be used to track promotional supplies across the supply chain, thus increasing the likelihood that in-store displays will be coordinated with advertising, which in turn ensures that maximum sales are generated by their marketing efforts (Collins, 2006e). By using the better supply chain visibility made possible by RFID, seasonal and perishable inventory can also be better controlled (Rutner et al., 2004; Kinsella, 2005), and fraud and counterfeiting can be reduced (Srivastava, 2004; Bacheldor, 2006b).

It is important to note that better supply chain visibility from RFID may not always lead to substantial performance improvements. As suggested by the last entry in the supply chain integration column on Figure 54, identifying the conditions of when RFID's visibility is truly beneficial in light of potential tradeoffs will help companies target their RFID investments more wisely. For example, Holmes (2001) showed conceptually and analytically that timely inventory data collection techniques such as RFID are especially beneficial to stores with high delivery frequencies, and so the two are mutually reinforcing. Despite this, it is possible that the incremental advantage of RFID compared to bar coding would not justify more frequent deliveries, given the rising costs of supply chain transportation and the fact that some vendors already deliver daily while using low-cost bar coding systems that provide adequate information. In other words, practical limits on supply chain delivery frequencies may diminish the realized benefits of RFID. This is analogous to the fact that this dissertation showed that RFID can provide reductions in mean flow time and proportion tardy for companies with low setup to processing time ratios, but practical limitations in material handling may inhibit the use of RFID for companies operating under those conditions. This dissertation made an important contribution by quantifying the material handling trade-off in factories that is necessary to achieve RFID benefits for various shop floor conditions. Similarly, future research can identify how trade-offs such as delivery frequencies should be managed when using RFID in supply chains.

As seen by the third column in Figure 54, RFID also offers significant potential improvements for retailers. The time necessary for customers to complete their checkouts and for stores to perform inventory auditing can be dramatically reduced (Srivastava, 2004; Angeles, 2005; O'Connor, 2005). Wal-Mart has already demonstrated how RFID can lead to fewer stockouts (Hardgrave et al., 2005). Continuous tracking and embedding RFID tags inside of product packaging enable better inventory control and reduced shrinkage (Srivastava, 2004; Kinsella, 2005). By tagging people or shopping carts, service providers can develop better understanding of flows through the servicescape, which can in turn lead to improved service, pricing, and sales (Srivastava, 2004; Larson et al., 2006).

If consumers are willing to leave RFID tags on purchased products after the sale, manufacturers could have far better information about how their products are used, which might enable design improvements. By placing comprehensive bill of material (part content) information on RFID tags (or cross-referencing such component information to the tags from a central database), recycling will be much more easy and accurate

(Parlikad, McFarlane, Fleisch, and Gross, 2003; Schmitt et al., 2006). Better traceability could reduce some of the hassle and costs associated with recalls because the scope of affected products could be more precisely defined (McFarlane and Sheffi, 2003; Schmitt et al., 2006).

LIST OF REFERENCES

Adams, J., E. Balas and D. Zawack (1988). "The Shifting Bottleneck Procedure for Job Shop Scheduling." Management Science 34(3): 391-401.

Alper, A. (2006). "Nissan Accelerates Into Active RFID Fast Lane." accessed January 6, 2007, from http://www.managingautomation.com/maonline/news/read/Nissan_Accelerates_Into_Active_RFID_Fast_Lane_26123.

Alvarez, G. (2005). "RFID, fast follower strategies don't mix." accessed December 5, 2006, from http://informationweek.com/shared/printableArticle.jhtml?articleID=60403588.

Anand, G. and P. T. Ward (2004). "Fit, Flexibility and Performance in Manufacturing: Coping with Dynamic Environments." Production & Operations Management 13(4): 369-385.

Angeles, R. (2005). "RFID technologies: supply-chain applications and implementation issues." Information Systems Management 22(1): 51-65.

Asif, Z. and M. Mandviwalla (2005). "Integrating the supply chain with RFID: a technical and business analysis." Communications of the Association for Information Systems 15: 393-426.

Bacheldor, B. (2005). "RFID pain now, rewards to come." InformationWeek: 51-52.

Bacheldor, B. (2006a). "Forecast Indicates Strong RFID Demand by Heavy Manufacturing." accessed January 5, 2007, from http://www.rfidjournal.com/article/articleprint/2652/-1/1/.

Bacheldor, B. (2006b). "Report sees sharp rise in pharma RFID." accessed December 5, 2006, from http://www.rfidjournal.com/article/articleview/2319/1/8/.

Bacheldor, B. (2006c). "Toshiba Laptop Plant Raises Productivity." accessed January 5, 2007, from http://www.rfidjournal.com/article/articleprint/2817/-1/1/.

Bacheldor, B. (2006d). "Transmission company puts RFID system into gear." accessed August 22, 2006, 2006, from http://www.rfidjournal.com/article/articleprint/2571/-1/1/.

Baker, K. R. (1984). "Sequencing rules and due-date assignments in a job shop." Management Science 30(9): 1093-1104.

Baker, K. R. and J. J. Kanet (1983). "Job shop scheduling with modified due dates." Journal of Operations Management 4(1): 11-22.

Banks, J., J. S. Carson II, B. L. Nelson and D. M. Nicol (2001). Discrete-Event System Simulation. Upper Saddle River, NJ: Prentice Hall.

Barcikowski, R. S. and R. R. Robey (1984). "Decisions in Single Group Repeated Measures Analysis Statistical Tests and Three Computer Packages." The American Statistician 38(2): 148-150.

Barlas, D. (2004). "Making RFID efficient." accessed December 5, 2006, from http://www.line56.com/articles/default.asp?ArticleID=5547.

Barlow, R. D. (2005). "Auto ID Tug-of-War: Bar Coding Vs. RFID." Healthcare Purchasing News(June): 12-14.

Barlow, R. D. (2006). "Reality check: debunking bar coding's popular myths and perceptions." Healthcare Purchasing News 30(7): 54-57.

Barut, M., R. Brown, N. Freund, J. May and E. Reinhart (2006). "RFID and Corporate Responsibility: Hidden Costs in RFID Implementation." Business and Society Review 111(3): 287-303.

Bean, L. (2006). "RFID: Why the worry?" The Journal of Corporate Accounting & Finance 17(5): 3-13.

Biskup, D. and M. Feldmann (2006). "Lot Streaming with Variable Sublots: An Integer Programming Formulation." Journal of the Operational Research Society 57: 296-303.

Bonasia, J. (2006). RFID Puts Forklift At Next Level. Investor's Business Daily: A4.

Borriello, G. (2005). "RFID: Tagging the world." Communications of the ACM 48(9): 34-37.

Bragg, D. J., E. A. Duplaga and R. J. Penlesky (2005). "Impact of product structure on order review evaluation procedures." Industrial Management & Data Systems 105(3): 307-324.

Brusey, J., M. Fletcher, M. Harrison, A. Thorne, S. Hodges and D. McFarlane (2003). Auto-ID Based Control Demonstration Phase 2: Pick and Place Packing with Holonic Control. Cambridge, United Kingdom, Auto-ID Centre Institute for Manufacturing, University Of Cambridge: 1-20.

Byrnes, J. (2003). "Who will profit from auto-ID?" accessed August 28, 2006, from http://workingknowledge.hbs.edu/item.jhtml?id=3651&t=dispatch.

Byrnes, J. (2004). "Are you aiming too low with RFID?" accessed December 5, 2006, from http://hbswk.hbs.edu/archive/4107.html.

Carr, N. G. (2004). Does IT matter? Information technology and the corrosion of competitive advantage. Boston: Harvard Business School Press.

Caulfield, B. (2003). "Giving Customers a Voice." Business 2.0 4(8): 60-62.

Chang, J. H. and H. N. Chiu (2005). "A comprehensive review of lot streaming." International Journal of Production Research 43(8): 1515-1536.

Chappell, G., L. Ginsburg, P. Schmidt, J. Smith and J. Tobolski (2003). Auto-ID on the line: the value of auto-ID technology in manufacturing, Auto-ID Center.

CIO Magazine (2003). "IT reloaded." CIO Magazine 16(19): 62-65.

Cohen, J. (1994). "The earth is round ($p < .05$)." American Psychologist 49(12): 997-1003.

Cohen, J., P. Cohen, S. G. West and L. S. Aiken (2003). Applied multiple regression/correlation analysis for the behavioral sciences. Mahwah, NJ: Lawrence Erlbaum Associates.

Collins, J. (2006a). "BT auto-ID launches service for food supply chain." accessed August 22, 2006, 2006, from http://www.rfidjournal.com/article/articleprint/2526/-1/1/.

Collins, J. (2006b). "DaimlerChrysler Putting RFID Tags in Kanban Cards." accessed January 6, 2007, from http://www.rfidjournal.com/article/articleprint/2405/-1/1/.

Collins, J. (2006c). "MTU Examines RFID to Keep Its Production Line Rolling." accessed January 6, 2007, from http://www.rfidjournal.com/article/articleview/211?Redirect=/article/articleview/2418.

Collins, J. (2006d). "P&G finds RFID 'sweet spot'." accessed December 5, 2006, from http://www.rfidjournal.com/article/articleview/2312/1/1/.

Collins, J. (2006e). "P&G finds RFID 'sweet spot'." accessed August 22, 2006, from http://www.rfidjournal.com/article/articleview/2312/1/1/.

Control Engineering (2005). "RFID on the Production Line." Control Engineering: 34-43.

Craig, T. (2004). "Wal-Mart and RFID - It's Like Retail Link Deja-Vu All Over Again." DSNRetailingToday(January 26): 13.

Curtin, J., R. J. Kauffman and F. J. Riggins (2007). "Making the 'most' out of RFID technology: a research agenda for the study of the adoption, usage and impact of RFID " Information Technology and Management.

Das, A. (2001). "Towards theory building in manufacturing flexibility." International Journal of Production Research 39(18): 4153-4177.

Dighero, C., J. Kellso, D. Merizon, M. Murphy and R. Tyo (2005). "RFID: the real and integrated story." Intel Technology Journal 9(3): 247-257.

Dudley, N. A. (1963). "Work-Time Distributions." International Journal of Production Research 2(2): 137-144.

EPCglobal (2006). EPC Changing the CPG Industry: Electronic Proof of Delivery (EPOD).

Ericson, J. (2004a). "RFID and logistics assets." accessed December 5, 2006, from http://www.line56.com/articles/default.asp?ArticleID=5792.

Ericson, J. (2004b). "RFID: how fast, how far?" accessed December 5, 2006, from http://www.line56.com/articles/default.asp?articleID=5640&TopicID=2.

Ericson, J. (2004c). "RFID: stay on message." accessed December 5, 2006, from http://www.line56.com/print/default.asp?ArticleID=5445&TopicID=2.

Evans, B. (2005). "Business Technology: Implementing RFID Is A Risk Worth Taking." accessed January 4, 2006, from http://www.informationweek.com/shared/printableArticle.jhtml?articleID=164302282.

Feare, T. (2000). "Pump Up the Volume." Modern Materials Handling: 55-59.

Field, A. (2005). Discovering Statistics Using SPSS for Windows. London, England: Sage Publications.

Fleisch, E., J. Ringbeck, S. Stroh, C. Plenge and M. Strassner (2004). From operations to strategy: the potential of RFID for the automotive industry, University of St. Gallen.

Florence, D. and C. Queree (1993). "Traceability - problem or opportunity?" Logistics Information Management 6(4): 3-8.

Food Manufacture (2005). "RFID early adopters won't share." Food Manufacture 80(5): 23.

Forger, G. (2005). "How Real Time Changes Operations." accessed January 6, 2007, from http://www.mmh.com/article/CA623770.html?industryid=21966.

Garcia, A., D. McFarlane, M. Fletcher and A. Thorne (2003). Auto-ID in Materials Handling. Cambridge, United Kingdom, Auto-ID Centre Institute For Manufacturing, University Of Cambridge: 1-20.

Gaukler, G. M. (2005). RFID in Supply Chain Management. Management Science and Engineering. Palo Alto, CA, Stanford University. Doctor of Philosophy.

Gaukler, G. M. and W. H. Hausman (under review). RFID in assembly operations: process and quality savings.

Gerwin, D. (1993). "Manufacturing Flexibility: A Strategic Perspective." Management Science 39(4): 395-410.

Gilmore, D. and M. Fralick. (2005). "10 things necessary for RFID/EPC to thrive." accessed December 5, 2006, from http://www.scdigest.com/assets/reps/SCDigest_RFID_EPC_to_Thrive.PDF.

Girden, E. R. (1992). ANOVA: repeated measures. Newbury Park, CA: SAGE Publications.

Global Commerce Initiative and IBM (2005). EPC: a shared vision for transforming business processes, Global Commerce Initiative and IBM.

Greengard, S. (2004). "The New Frontier in Supply Chain Management." Business Finance September.

Greenhouse, S. W. and S. Geisser (1959). "On methods in the analysis of profile data." Psychometrika 24(2): 95-112.

GS1 Canada (2002). Bar coding for designers, printers, & packagers, GS1 Canada.

Gunasekaran, A. and E. W. T. Ngai (2005). "Build-to-order supply chain management: a literature review and framework for development." Journal of Operations Management 23(5): 423-451.

Hair, J., Joseph F., R. E. Anderson, R. L. Tatham and W. C. Black (1998). Multivariate analysis. Upper Saddle River, NJ: Prentice-Hall.

Hall, K. (2006). "No One Does Lean Like the Japanese." Business Week(3992): 40-41.

Hannon, D. (2005). "What you need to know about RFID for inbound logistics." Purchasing(March 5): 46-49.

Hardgrave, B. C., M. Waller and R. Miller (2005). Does RFID reduce OOS? A preliminary analysis, University of Arkansas.

Hassan, T. and S. Chatterjee (2006). A Taxonomy for RFID. Hawaii International Conference on System Sciences, Hawaii.

Hayes, R. H. and G. P. Pisano (1996). "Manufacturing strategy: at the intersection of two paradigm shifts." Production and Operations Management 5(1): 25-41.

Hayes, R. H. and S. G. Wheelwright (1979). "The Dynamics of Process-Product Life Cycles." Harvard Business Review: 127-136.

Hays, W. L. (1994). Statistics. Fort Worth, TX: Harcourt.

Heim, G. (2006). Conversation at 2006 Annual Decision Sciences Institute Conference. San Antonio, TX.

Higgins, L. N. and T. Cairney (2006). "RFID Opportunities and Risks." The Journal of Corporate Accounting & Finance 17(5): 51-57.

Hill, J., Sidney (2004). "The "other" use of RFID." MSI 22(9): 46-48.

Hill Jr., S. (2004). "The "other" use of RFID." MSI 22(9): 46-48.

Hoffman, W. (2005). "Shippers still reject RFID." Traffic World 269(46): 22-22.

Hoffman, W. (2006). "Wanted: RFID 'paradigm shift'." Gulf Shipper 17(24): 60.

Holmes, T. J. (2001). "Bar codes lead to frequent deliveries and superstores." RAND Journal of Economics 32(4): 708-725.

Hopp, W. J. and M. L. Spearman (2001). Factory Physics. New York, NY: Irwin McGraw-Hill.

Hou, J.-L. and C.-H. Huang (2006). "Quantitative performance evaluation of RFID applications in the supply chain of the printing industry." Industrial Management & Data Systems 106(1): 96-120.

Ittner, C. D. and J. P. MacDuffie (1995). "Explaining Plant-Level Differences in Manufacturing Overhead Structural and Executional Cost Drivers in the World Auto Industry." Production & Operations Management 4(4): 312-334.

Jacobs, F. R. and D. J. Bragg (1988). "Repetitive Lots: Flow-Time Reductions through Sequencing and Dynamic Batch Sizing." Decision Sciences 19(2): 281-294.

Jacobson, S. (2006). Manufacturers plan increased compliance investments for traceability in 2006, AMR Research.

Jayamohan, M. S. and R. Chandrasekharan (2000). "New dispatching rules for shop scheduling: a step forward." International Journal of Production Research 38(3): 563-586.

Joshi, Y. V. (2000). Information visibility and its effect on supply chain dynamics. Mechanical Engineering. Cambridge, Massachusetts, Massachusetts Institute of Technology. Master of Science: 67.

Kang, Y. and S. B. Gershwin (2005). "Information inaccuracy in inventory systems: stock loss and stockout." IIE Transactions 37(9): 843-859.

Kärkkäinen, M. (2003). "Increasing Efficiency in the Supply Chain for Short Shelf Life Goods Using RFID Tagging." International Journal of Retail & Distribution Management 31(10): 529-536.

Kärkkäinen, M. and J. Holmström (2002). "Wireless product identification: enabler for handling efficiency, customisation and information sharing." Supply Chain Management: An International Journal 7(4): 242-252.

Kelton, W. D., R. P. Sadowski and D. T. Sturrock (2004). Simulation with Arena. New York: McGraw-Hill Higher Education.

Keppel, G. (1991). Design and Analysis: A Researcher's Handbook. Upper Saddle River, New Jersey: Prentice-Hall.

Kher, H. V., M. K. Malhotra and D. C. Steele (2000). "The effect of push and pull lot splitting approaches on lot traceability and material handling costs in stochastic flow shop environments." International Journal of Production Research 38(1): 141-160.

Kinsella, B. (2005). "Delivering the Goods." Industrial Engineer 37(3): 24-30.

Kirk, R. E. (1995). Experimental Design: Procedures for the Behavioral Sciences. Pacific Grove, CA: Brooks/Cole Publishing Company.

Kohn, W., V. Brayman and J. Littleton (2005). "Repair-control of enterprise systems using RFID sensory data." IIE Transactions 37(4): 281-290.

Koste, L. L., M. K. Malhotra and S. Sharma (2004). "Measuring dimensions of manufacturing flexibility." Journal of Operations Management 22(2): 171-196.

Kropp, D. H., T. L. Smunt and A. H. Buss (1988). Lot-Splitting Performance Under Varying Flow Dominance Conditions. ORSA/TIMS Jolnt National Mccting. Denver, CO.

Lahiri, S. (2006). RFID sourcebook. Upper Saddle River, NJ: IBM Press.

Lai, F., J. Hutchinson and G. Zhang (2005). "Radio frequency identification (RFID) in China: opportunities and challenges." International Journal of Retail & Distribution Management 33(12): 905-916.

Langer, N., C. Forman, S. Kekre and A. Scheller-Wolf (2007). Assessing the Impact of RFID on Return Center Logistics. Pittsburgh, PA, Carnegie Mellon University.

Lapide, L. (2004). "RFID: What's in it for the forecaster?" The Journal of Business Forecasting 23(2): 16-19.

Larson, J. S., E. T. Bradlow and P. S. Fader (2006). "An exploratory look at supermarket shopping paths." International Journal of Research in Marketing 22: 395-414.

Law, A. M. and W. D. Kelton (2000). Simulation modeling and analysis. New York: McGraw-Hill Higher Education.

Lee, H. L. and S. Whang (2005). "Higher supply chain security with lower cost: Lessons from total quality management." International Journal of Production Economics 96: 289-300.

Lejmi, T. and I. Sabuncuoglu (2002). "Effect of load, processing time and due date variation on the effectiveness of scheduling rules." International Journal of Production Research 40(4): 945-974.

Li, S. and J. K. Visich (2006). "Radio frequency identification: supply chain impact and implementation challenges." International Journal of Integrated Supply Management 2(4): 407-424.

Litchfield, J. and R. Narasimhan (2000). "Improving job shop performance through process queue management under transfer batching." Production and Operations Management 9(4): 336-348.

Lockwood, W. T., F. Mahmoodi, R. A. Ruben and C. T. Mosier (2000). "Schedul ing unbalanced cellular manufacturing systems with lot splitting." International Journal of Production Research 38(4): 951-965.

Markelevich, A. and R. Bell (2006). "RFID: the changes it will bring." Strategic Finance 88(2): 46-49.

Mathews, P. (2005). Design of experiments with MINITAB. Milwaukee, WI: Quality Press.

McClenahen, J. S. (2005). "Wal-Mart's Big Gamble." Industry Week 254(4): 42-49.

McCrea, B. (2006). "Where's the ROI?" Logistics Management 45(11): 49.

McFarlane, D. and Y. Sheffi (2003). "The impact of automatic identification on supply chain operations." International Journal of Logistics Management 14(1): 1-17.

McIntyre, T. (2006). "Adding RFID to Ford's Supply Chain." accessed January 12, 2007, from http://www.rfidjournal.com/article/articleview/2249/1/128/.

Menges, K. (2006). RFID: Beyond Compliance. Erie, PA, Center for eBusiness and Advanced IT: 1-3.

Miceli, J. (2005). "Harness the power of real-time data." Paperboard Packaging 90(8): Special Section 19s-21s.

Michel, R. (2006). "Adaptive Manufacturing Moves In." accessed January 6, 2007, from http://www.mmh.com/article/CA6369919.html.

Monahan, G. E. and T. L. Smunt (1999). "Processes with Nearly Sequential Routings: A Comparative Analysis." Journal of Operations Management 17: 449-466.

Murphy-Hoye, M., H. L. Lee and J. Rice, James B. (2005). "A real-world look at RFID." Supply Chain Management Review 9(5): 18-26.

Murphy, C. (2005a). "Real-world RFID: Wal-Mart, Gillette, and others share what they're learning." accessed December 5, 2006, from http://www.informationweek.com/showArticle.jhtml?articleID=163700955.

Murphy, J. V. (2005b). "On the edge: understanding the RFID framework." accessed December 5, 2006, from http://www.glscs.com/archives/02.05.rfid.htm?adcode=10.

Narsing, A. (2005). "RFID And Supply Chain Management: An Assessment Of Its Economic, Technical, And Productive Viability In Global Operations." The Journal of Applied Business Research 21(2): 75-79.

Navistar (2006). Personal communication.

Neil, S. (2006). "Marching Toward the RFID Business Case." Managing Automation December.

O'Connor, M. C. (2005). "Item tagging offers quick payback." accessed December 5, 2006, from http://www.rfidjournal.com/article/articleview/2041/1/1/.

O'Connor, M. C. (2006a). "RFID sees gains in health care." accessed December 5, 2006, from http://www.rfidjournal.com/article/articleview/2154/1/1/.

O'Connor, M. C. (2006b). "Satellite Equipment Center Automates Inventory Tracking." accessed December 29, 2006, from http://www.rfidjournal.com/article/articleprint/2876/-1/1/.

Ollivier, M. (1995). "RFID enhances material handling." Sensor Review 15(1): 36-39.

Palmer, R. C. (1995). The bar code book: reading, printing, specification, and application of bar code and other machine readable symbols. Peterborough, NH: Helmers Publishing.

Parlikad, A. K., D. McFarlane, E. Fleisch and S. Gross (2003). The role of product identity in end-of-life decision making, Auto-ID Centre.

Petroff, J. N. and A. V. Hill (1991). "A framework for the design of lot-tracing systems for the 1990's." Production & Inventory Management Journal 32(2): 55-61.

Prater, E., G. V. Frazier and P. M. Reyes (2005). "Future impacts of RFID on e-supply chains in grocery retailing." Supply Chain Management: An International Journal 10(2): 134-142.

Quinn, F. J. (2005). "Setting the standards: an interview with Mike Meranda." Supply Chain Management Review 9(7): 34-38.

Raman, A., N. DeHoratius and Z. Ton (2001). "Execution: The Missing Link In Retail Operations." California Management Review 43(3): 136-152.

Riggins, F. J. and K. T. Slaughter (2006). The Role of Collective Mental Models in IOS Adoption: Opening the Black Box of Rationality in RFID Deployment. Hawaii International Conference on System Sciences, Hawaii.

Roberti, M. (2006). "Taking RFID's Temperature." accessed January 4, 2007, from http://www.rfidjournal.com/article/articleprint/2743/-1/128/.

Roberts, C. M. (2006). "Radio frequency identification (RFID)." Computers & Security 25(1): 18-26.

Rockwell Automation. (2006). "Arena leads the way!" accessed August 4, 2006, from http://www.arenasimulation.com/news/default.asp.

Rohleder, T. R. and G. Scudder (1993). "A Comparison of Order-Release and Dispatch Rules for the Dynamic Early Tardy Problem." Production and Operations Management 2(3): 221-238.

Rothfeder, J. (2005). "What's Wrong with RFID?" CIO Insight(42): 45-53.

Rutner, S., M. A. Waller and J. T. Mentzer (2004). "A practical look at RFID." Supply Chain Management Review 8(1): 36-41.

Salegna, G. J. and P. S. Park (1996). "Workload smoothing in a bottleneck job shop." International Journal of Operations & Production Management 16(1): 91-110.

Schmenner, R. W. and M. V. Tatikonda (2005). "Manufacturing process flexibility revisited." International Journal of Operations & Production Management 25(12): 1183-1189.

Schmitt, P., F. Michahelles and E. Fleisch (2006). An adoption strategy for an open RFID standard - potentials for RFID in the automotive aftermarket, Auto-ID Labs.

Schuster, E. W., T. A. Scharfeld, P. Kar, D. L. Brock and S. J. Allen (2004). "The next frontier: how auto-ID could improve ERP data quality." Cutter IT Journal 17(9): 12-18.

Scott, S. (2005). "Enabling supply-chain strategies with RFID." Logistics & Transport Focus 7(7): 41-44.

Shister, N. (2005). "RFID: taking stock of the Wal-Mart pilot." World Trade 18(8): 38-42.

Sliwa, C. (2004). "Sara Lee wrestles with RFID, looks for benefits." Computerworld 38(37): 22.

Sliwa, C. (2005a). "RFID vendor says tag prices won't drop to 10 cents until '07." accessed December 5, 2006, from http://www.computerworld.com/industrytopics/retail/story/0,10801,100230,00.html.

Sliwa, C. (2005b). "Suppliers eye RFID data, search for potential uses." Computerworld 39(10): 12-12.

Smunt, T. L., A. H. Buss and D. H. Kropp (1996). "Lot splitting in stochastic flow shop and job shop environments." Decision Sciences 27(2): 215-238.

Smyrlis, L. (2005). "Supply chain software: what's hot and what's not." Canadian Transportation & Logistics 108(3): 12-15.

Sridharan, V. and W. L. Berry (1990). "Freezing the master production schedule under demand uncertainty." Decision Sciences 21(1): 97-120.

Srivastava, B. (2004). "Radio frequency ID technology: the next revolution in SCM." Business Horizons 47(6): 60-68.

Steele, D. C. (1995). "A Structure for Lot-Tracing Design." Production & Inventory Management Journal 36(1): 53-59.

Steffansson, G. and B. Tilanus (2001). "Tracking and tracing: principles and practice." International Journal of Services Technology and Management 2(3/4): 187-206.

Stein, D. (1999). "Let the ERP Software Buyer Beware!" Midrange ERP(June/July): reprint available by contacting http://www.esresearchcorp.com/home/index.php.

Sullivan, S. (2007). bar coding time standard from RFID presentation at INFORMS / GENCO. K. Hozak.

SupplyChainDigest. (2006). "OK, Wal-Mart Needs RFID." accessed January 12, 2007, from http://www.scdigest.com/assets/NewsViews/06-07-21-2.cfm.

Suresh, N. C. and J. R. Meredith (1994). "Coping with the loss of pooling synergy in cellular manufacturing systems." Management Science 40(4): 466-483.

Sutton, N. (2005). "Panel urges suppliers to start developing their RFID strategies." Computing Canada 31(6): 8.

Swedberg, C. (2006). "MIT and IESE study shows RFID's value." accessed September 28, 2006, from http://www1.rfidjournal.com/article/view/2299/.

Swink, M. and W. H. Hegarty (1998). "Core manufacturing capabilities and their links to product differentiation." International Journal of Operations & Production Management 18(4): 374-396.

Tellkamp, C. (2006). The Impact of Auto-ID Technology on Process Performance – RFID in the FMCG Supply Chain. Graduate School of Business Administration, Economics, Law and Social Sciences (HSG). St. Gallen, Switzerland, University of St. Gallen. Doctor of Business Administration: 170.

Tellkamp, C., A. Angerer, E. Fleisch and D. Corsten (2004). "From pallet to shelf: improving data quality in retail supply chains using RFID." Cutter IT Journal 17(9): 19-24.

Terzi, S. and S. Cavalieri (2004). "Simulation in the supply chain context: a survey." Computers in Industry 53(1): 14.

Trebilcock, B. (2006). "The return on investment from RFID may be in the stores." accessed January 4, 2007, from http://www.mmh.com/article/CA6402751.html.

Trebilcock, R. (2005). "The Changing Face of Real Time." Modern Materials Handling: 24-28.

van Dorp, K.-J. (2002). "Tracking and tracing: a structure for development and contemporary practices." Logistics Information Management 15(1): 24-33.

Vijayaraman, B. S. and B. A. Osyk (2006). "An Empirical Study of RFID Implementation in the Warehousing Industry." The International Journal of Logistics Management 17(1): 6-20.

Vokurka, R. J. and S. W. O'Leary-Kelly (2000). "A review of empirical research on manufacturing flexibility." Journal of Operations Management 18(4): 485-501.

Wagner, B. J. and G. L. Ragatz (1994). "The impact of lot splitting on due date performance." Journal of Operations Management 12(1): 13-25.

Wessel, R. (2007). "DHL to Market RFID-enabled Smart Box." accessed January 15, 2007, from http://www.rfidjournal.com/article/articleview/2945/.

WinWare. (2006). "What RFID can (and can't) do to control indirect materials, tools and spare parts." accessed December 5, 2006, from http://www.reliableplant.com/article.asp?articleid=956.

Woods, J. (2003). Use RFID only if it's intrinsic to the business case. Stamford, CT, Gartner, Inc.

Woods, J. (2004). Heuristics for the profitable use of RFID. Stamford, CT, Gartner, Inc.

Woods, J. (2005). RFID enables sensory network strategies to transform industries. Stamford, CT, Gartner.

Wu, N. C., M. A. Nystrom, T. R. Lin and H. C. Yu (2006). "Challenges to global RFID adoption." Technovation 26: 1317-1323.

Wyld, D. C. (2006). "RFID 101: the next big thing for management." Management Research News 29(4): 154-173.

Xie, J., X. Zhao and T. S. Lee (2003). "Freezing the master production schedule under single resource constraint and demand uncertainty." International Journal of Production Economics 83(1): 65-84.

Yang, G. and S. L. Jarvenpaa (2005). Trust and Radio Frequency Identification (RFID) Adoption within an Alliance. Hawaii International Conference on System Sciences, Hawaii.

Zhang, Q., M. A. Vonderembse and J.-S. Lim (2003). "Manufacturing flexibility: defining and analyzing relationships among competence, capability, and customer satisfaction." Journal of Operations Management 21(2): 173-191.

Zhao, X. and T. S. Lee (1993). "Freezing the master production schedule for material requirements planning systems under demand uncertainty." Journal of Operations Management 11(2): 185-205.