Integrated Supply and Production Network Design

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Submitted to the Institute for Data, Systems and Society and the MIT Sloan School of Management in partial fulfillment of these requirements for the degrees of
Master of Science in Engineering Systems
and
Master of Business Administration
in conjunction with the Leaders for Global Operations Program at the
MASSACHUSETTS INSTITUTE OF TECHNOLOGY

June 2016
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Abstract

As Company X looks to improve customer service and deliver new growth opportunities, it is driving toward a more efficient, aligned and effective organization that eliminates waste through integration of its supply and production networks.

The current manufacturing system is optimized for high volume products with low demand variation signals, and is used for all products regardless of demand characteristics. The effects of such a system on the supply network are higher holding cost and stale inventory, while the effects on the business are lost sales and higher total delivered cost. A more responsive production system is an opportunity to reduce strain on the supply network, reduce total delivered cost and improve product fulfillment.

Analysis of a portfolio of products demonstrates two main findings: (1) considerable impact of inventory cost on the total delivered cost and (2) a definitive case for differentiated manufacturing strategy – for high and low volume products. Previously only manufacturing cost had been used to make the decision of which system might better fit the goals of providing products in a timely and cost efficient manner. However, the uncovering of the impact of inventory cost on the total delivered cost has challenged that perception.

An analysis was also performed on various algorithms which optimize (1) the product lot size and (2) job scheduling on machines. EOQ and a Mixed Integer Program were both analyzed for lot size determination, with the latter demonstrating more cost efficient and production efficient results due to more flexibility with the time scale and the consideration of manufacturing capacity. Finally, a couple of bin packing algorithm heuristics were tested for job scheduling. The results demonstrated significant time savings in job scheduling and have highlighted the need to automate the scheduling process.
Acknowledgements

The author wishes to acknowledge the Leaders for Global Operations Program for its support of this work.

None of this work would have been possible without the support of the LGO program, my faculty advisors, the team at host Company X, my friends and my family.

A big thanks to the LGO program – staff and classmates alike – for providing me with the support and guidance I needed, and shaping my experience at MIT over the last two years. It has been an incredible experience and I am so thankful to have had the chance to join this small yet incredible, powerful and supportive LGO community.

A huge thank you to my advisors, Don Rosenfield and David Simchi-Levi, who have graciously provided their support to my work and have guided me through the integration of classroom and real world learning the result of which is the thesis work you are about to read.

This project would not have been possible without the generous support of my host company. A huge thanks to the project sponsors, my project mentor, and all those who have provided me with their time and support throughout the project. The advice I obtained was indispensable both to the success of the project and to my growth as a professional. I hope to be half as good a mentor as all of you have been to me throughout my six months at Company X.

Finally and most importantly I extend an enormous thank you to my parents, Dania and Ravil, and my partner, Sergio, for their continued support in all the crazy adventures I undertake. Thanks to you I know I can always make it on my own but it’s so much more fun with you coming along for the ride. You’ve been there for all the happy moments, like when I first announced my acceptance to LGO, and all the tough moments, like when stress of school piled on. Thank you for surviving these past two years by my side and providing me with the encouragement and support I sometimes forgot I needed. This has been an incredible journey. Thank you for coming along for the ride!
Contents

List of Figures .................................................................................................................................. 7
List of Tables .................................................................................................................................. 8

Chapter 1 ........................................................................................................................................ 9
1.1 Company X ...................................................................................................................... 9
1.2 Project Motivation ......................................................................................................... 10
1.3 Project Objectives .......................................................................................................... 10
1.4 Thesis Hypothesis .......................................................................................................... 10
1.5 Methodology and Approach .......................................................................................... 11

Chapter 2 ...................................................................................................................................... 15
2.1 Decision making frameworks .................................................................................... 15
2.2 Lot size problem ............................................................................................................ 17
  2.2.1 Diverse landscape of lot size problems ............................................................... 17
  2.2.2 Lot size model review ........................................................................................... 19
2.3 Scheduling algorithms ............................................................................................... 21

Chapter 3 ...................................................................................................................................... 23
3.1 Existing performance metrics .................................................................................... 23
  3.1.1 Manufacturing metrics of success .................................................................... 24
  3.1.2 Impact of manufacturing metrics on Supply Chain ........................................... 25
3.2 Production planning process ...................................................................................... 26
3.3 Summary ......................................................................................................................... 27

Chapter 4 ...................................................................................................................................... 28
4.1 Theory ............................................................................................................................ 28
  4.1.1 Total delivered cost ............................................................................................. 29
4.2 Results ............................................................................................................................ 33
  4.2.1 Total Delivered Cost ........................................................................................... 33
  4.2.2 Product variety as a function of capacity ........................................................... 37
  4.2.3 Differentiated Manufacturing Channels ............................................................. 38
  4.2.4 Addressing market growth through differentiated sales channels .................... 39
  4.2.5 Lead time improvement ....................................................................................... 40
4.3 Summary ........................................................................................................................ 42
List of Figures

FIGURE 1. THESIS PROCESS APPROACH .................................................................12
FIGURE 2. DATA SOURCES AND MODEL RELATIONSHIP ..................................14
FIGURE 3. TECHNICAL STRUCTURE OF LOT SIZING PROBLEM ...................18
FIGURE 4. CONTENT-RELATED CLASSIFICATION OF LOT SIZING PROBLEM .......19
FIGURE 5. PRODUCTION COST PER UNIT VERSUS LOT SIZE. ASSUMPTIONS – SYSTEM CAPACITY IS CONSTANT IN BOTH SYSTEMS, PRODUCTION IS OVER 7 CONSECUTIVE DAYS, SAME PRODUCT ON BOTH SYSTEMS WITH THE SAME ANNUAL DEMAND .................................................................34
FIGURE 6. INVENTORY COST PER UNIT. INVENTORY COST INCLUDES CARRYING COST FOR THE LOT SIZE AND SAFETY STOCK, AS WELL AS COST OF CAPITAL DUE TO STORAGE. LOT SIZES ARE SPECIFIC TO SYSTEM A AND SYSTEM B .................................................................35
FIGURE 7. TOTAL DELIVER COST FOR SYSTEMS A AND B; INCLUDES CONVERSION COST AND INVENTORY COST .......36
FIGURE 8. STRATEGIC EFFICIENT FRONTIER ........................................................................38
FIGURE 9. SUMMARY OF VALUE STREAM MAP FOR SYSTEM A AND SYSTEM B. OVERALL, SYSTEM B WAS FASTER THAN SYSTEM A BETWEEN 4 TO 6 TIMES .................................................................40
FIGURE 10. GANTT CHART FOR 12 PRODUCTS WITH EOQ LOT SIZE AND LPT SCHEDULING ALGORITHMS ........51
FIGURE 11. GANTT CHART FOR 12 PRODUCTS WITH MIP LOT SIZE AND LPT SCHEDULING ALGORITHMS ........51
FIGURE 12. SENSITIVITY ANALYSIS WITH REGARDS TO DELTA IN INVENTORY COSTS ........................................53
FIGURE 13. SENSITIVITY ANALYSIS WITH REGARDS TO PRODUCTION COST ........................................54
List of Tables

TABLE 1. SAMPLE LEVEL DESIGN ..............................................................32
TABLE 2. PRODUCT SKU VARIETY IN RELATION TO LOT SIZE OVER A 7 DAY PERIOD ........................................38
TABLE 3. SUMMARY OF VARIOUS CRITERIA ACCOUNTED FOR IN DIFFERENT LOT SIZE ALGORITHMS ..................46
TABLE 4. ANNUAL COSTS FOR EOQ AND MIP ........................................52
Chapter 1

Introduction

Like many other large manufacturing companies, Company X is adapting to rapidly evolving customer needs. It has a strong focus on operational improvement and has previously collaborated on two other operations projects with MIT’s Leaders for Global Operations (LGO) Program. The goals of this third project instalment are: (1) to develop a new production allocation decision framework which will enable the company to better make decisions about where and how to make their products, and (2) to improve upon the existing production planning structure in order to optimize product flow through a specific manufacturing facility.

1.1 Company X

The research described in the contents of this work was conducted with cooperation from an undisclosed “Company X.” Company X is a Fortune 500 company with a global manufacturing and customer footprints. It operates in a challenging environment of increasingly diverse product portfolios, high capital expenditures and complex manufacturing. The company is currently undergoing several operational improvement projects in order to better serve its customers and deliver new growth opportunities. This study will focus on the company’s developments in the manufacturing sector. The company will be referred to as “Company X” throughout this work.
1.2 Project Motivation

In order to meet customer expectations in a dynamic market, Company X has been proliferating its product portfolio. This has led to lower demand per individual product which consequently increases manufacturing complexity and cost. The existing manufacturing system was developed for large volume products, taking advantage of economies of scale and the concept of “make-to-stock.” The expanding array of products with lower demand volumes but higher value added is not well served under this traditional manufacturing structure. It struggles to provide the necessary product diversity in a timely manner that customers expect and increases total delivered cost for the company. There is an opportunity for the company to improve upon the traditional manufacturing system in order to better serve its customers and itself.

1.3 Project Objectives

Company X is exploring an alternative production and supply chain approaches which may better fulfill low volume demand and deliver new growth opportunities. The goals of this project are (1) to evaluate production allocation under the alternative approach and (2) to optimize production flow through a system which efficiently delivers lower volume items.

The traditional manufacturing system is the starting point for production allocation analysis. The current strategy and performance metrics are the baseline for a model which explores alternative evaluative criteria for success in a manufacturing setting. System capacity, conversion and inventory costs, and lead time are analyzed in relation to demand volume and manufacturing lot size, and serve as key elements in developing the production allocation model.

Additionally, the current production planning model is used as a comparison to a newly developed production planning approach which is aimed at improving product flow within a specific manufacturing system.

1.4 Thesis Hypothesis

This work addresses two hypotheses: (1) a new production allocation decision framework can be implemented across the company to better serve Company X's goals and customer needs, and (2)
the use of optimization techniques in production planning will result in significant delivered cost and time savings.

This study will serve to demonstrate that there is no “one size fits all” solution for Company X with regards to product manufacturing. Whereas the traditional production structure works well for large volume, low variable products, it may not be a good manufacturing fit for lower volume products. There remains a question of which items specifically should be produced under the traditional structure, and which criteria qualifies these products for traditional manufacturing.

This thesis will also address the manual production planning methods which are currently implemented company wide. Manual manipulation of inputs does not guarantee optimal production plans but today the decision of when, where and how much of each product to make largely depends on experience and manual heuristics developed by plants and production planners. There is already a push from supply chain side of the company to implement optimization techniques. This work hypothesizes that there are also significant benefits to implementing optimization within the manufacturing sector.

1.5 Methodology and Approach

This project consists of five phases (refer to Figure 1). The first phase is defining the objective and setting cadence and expectations for the allotted project time. Reviewing the past two projects and conversations with various stakeholders is key to understanding the current state of manufacturing and recognizing where further analysis is necessary. The first LGO project at Company X examined an integrated manufacturing and supply chain system with a specific goal of evaluating various supply chain strategies in order to minimize the total landed cost. The outcome was a mathematical model which enabled the company to make better informed strategic decisions in the design and implementation of its manufacturing and supply chains based on the total landed cost variable [1]. The second LGO project follows up on the integrated manufacturing and supply chain system thinking, focusing on redesigning of the supply chain. The project studies a segmented supply chain system which segregates products based on demand characteristics and through the redesigned supply chain network demonstrates a reduction in sensitivity to supply and demand at the same time as realizing cost reductions [2]. After reviewing the area of study and the final outcome of each of the past two projects, we
observe the recurring theme of an integrated manufacturing and supply chain system. Conversations with stakeholders within Operations and specific region markets further highlight the need for integrated system thinking. Since the focus of the previous two projects had been on supply chain strategies, there are opportunities to investigate improvements within other parts of the company including manufacturing, integration of manufacturing with supply chain, and system wide integration (raw materials procurement to sales). Due to ongoing companywide improvements within the manufacturing sector, we decided to focus on opportunities for improvement in manufacturing while at the same time keeping in mind the integrated manufacturing and supply chain approach examined in the previous two LGO projects. In order to further define the objective we also determined key performance metrics (KPIs) for both manufacturing and supply chain. Manufacturing specifically placed an importance on conversion cost and overall equipment efficiency, while supply chain highlighted the significance of inventory cost and lead time. Both cited protecting product quality as a key and primary goal. System capacity is also identified as an important factor in manufacturing planning (it is not a KPI metric). These serve as a basis for the production allocation model development and will discussed in more detail in Chapter 4. Finally, lot size, cycling and scheduling are identified as potential improvement opportunities for the production planning objective.

![Figure 1. Thesis process approach.](image)

The second phase of the project requires data collection through leveraging various data sources (see Figure 2). This is done primarily with the help of main stakeholders within manufacturing and supply chain who have direct access to the Supply Chain and Plant Production databases. Plant production data such as cycle time, lead time, takt time, etc. is collected for a number of facilities and an average is used for the purposes of model creation. A similar approach is taken
with supply chain and capacity planning records. Financial data collection posed the most difficulty in this stage and was finally resolved through a comparison study and several assumptions (supported by stakeholders within Finance and Operations).

Stage three analyzes the data previously collected and develops a preliminary model to address the production allocation objective. Initial analysis of plant production data includes plant capacity, conversion cost and lead time within the preliminary model. The effect of a capacity constrained system on product variety and manufacturing non-value added time at various stages of the production process is incorporated into the analysis. Parallel analysis of supply chain and capacity planning data demonstrates inventory cost as an important but overlooked factor of total delivered product cost. During this phase optimization techniques to address the second objective are also researched. Several models for lot size optimization are identified, including Economic Order Quantity and a Mixed Integer Program, which will be further discussed in Chapter 5. Scheduling algorithms are also explored but pose a challenge as most need a heuristic since the problem is NP hard and lies outside of practical application. Several heuristics are identified and developed for application (see Chapter 5).

The fourth stage gathers feedback from various stakeholders in the company as well as MIT LGO academic advisors. The primary objective of this stage is to test the models and to improve their interface in order to facilitate the application of the models and their concepts within the company. The production allocation model's interphase is encoded into Microsoft Excel while the production planning model uses Python and Microsoft Excel.

The final stage of the project presents the final models to the key stakeholders involved in the project and advocates for the concepts within the models as well as their application within Company X. During this phase key obstacles to implementation are discussed with stakeholders and final recommendations with regards to project objectives are presented both as a written report and a final presentation.
Figure 2. Data sources and model relationship.
Chapter 2

Literature Review

This research work will cover decision making frameworks for production allocation and production planning. Decision making can take a form of quantitative and qualitative decisions, and understanding the appropriate approach can be difficult. There exist several frameworks and analyses which can help in how to approach the problem and these will be discussed in this section. Production planning is a more quantitative approach and it is comprised of three main domains – long term, medium term and short term [3]. This thesis examines the methods for making decisions at the medium and short term horizons, specifically decisions regarding production lot size and job sequencing at the machine level in the workshop. The following literature review will discuss existing methods in determining the optimal production lot size. We will also examine the current solution methods for job scheduling at the machine level. Some of these ideas will be applied within the context of this thesis while others will be used as a reference and scope for future work.

2.1 Decision making frameworks

Decision making is a daily occurrence in the manufacturing setting. Previous work between LGO and Company X used quantitative techniques to make the decision of where to place various manufacturing facilities within the US region [1]. This thesis examines the decision making process regarding focusing manufacturing technology and systems to appropriate product classes. We found little information relating to this discussion topic. Most of the existing research covers decision making with regards to location of manufacturing sites and investment
opportunities. Although these works do not directly apply to the decision making process we are investigating, we think there are some valuable conclusions which may be applied to our own efforts.

There are no easy solutions when it comes to any type of decision making; however there exist several decision making frameworks which can be used as a reference for understanding how to approach our specific problem. Frank et al. note that both qualitative and quantitative criteria should be used in decision making but most investment decisions are made with economic criteria in mind, using little, if at all, consideration of qualitative criteria. They note that there are three criteria essential in any decision making – understanding the strategic advantage of the decision toward long term competitiveness, understanding the effect of the decision on internal and external clients (specifically with related to service or product quality), and computing the economic gains of the decision \[^4\]. There are significant difficulties in measuring qualitative criteria such as changes in perception from clients or understanding the strategic advantages in the competitiveness, and Frank et al. propose one method which quantifies these criteria with an integrated matrix approach.

Cohen and Lee specifically examine ways to link decision making and performance in an integrated production-distribution systems \[^5\]. They propose a model to answer two main questions – (1) how can production and distribution policies be coordinated to achieve synergies and performance, and (2) how do service level requirements affect costs, lead time and flexibility. To answer these questions they innovate on existing segregated models and formulate a single integrated quantitative model which links supply chain interactions and production and material procurement activities. The model is broken into interrelated submodels and the optimal ordering policies are resolved through minimizing the sum of all the submodels' costs together. They conclude that there exist tradeoffs between manufacturing and distribution costs (cost of holding inventory and cost of production), and ultimately the optimal strategic policies depend on the companies' priorities due to competitive pressures.

Chai et al. study the decision making process regarding the location of manufacturing facilities in the pharmaceutical industry \[^6\]. They note that this type of decision primarily examines at the benefits obtained at each site, and they break down these benefits into four main categories – site capabilities, network configuration capabilities, network coordination capabilities, and financial capabilities. Site capabilities include plant site advantages such as flexibility, knowledge and quality. Network level capabilities include ability to access strategic...
targets (desired markets), proximity to suppliers, and abilities of economies of scope or scale. Finally the financial advantages are abilities to lower cost and better manage cash flows. Chai et al. conclude that decision makers value single site benefits more than network wide benefits; however, taking a network perspective and understanding network wide benefits can add very significant strategic advantages to decision making.

Finally, Youssef et al. examine the production allocation decision between make to order (MTO) and make to stock (MTS) within a single facility [7]. They observe that “the priority allocation for multi-item manufacturing systems is known to be significant with respect to inventory costs,” and propose a non-linear integer quantitative model which minimizes average holding cost under a delivery fill constraint for each product.

2.2 Lot size problem

"Making the right decisions in lot sizing will affect directly the system performance and its productivity, which are important for a manufacturing firm’s ability to compete in the market.” [3]

2.2.1 Diverse landscape of lot size problems

Since the first publication of the Ford Whitman Harris’ Economic Order Quantity model in 1913, the lot sizing problem has been studied extensively within the production planning domain [8]. As Karimi et al. note “lot sizing is one of the most important and also one of the most difficult problems in production planning” [3]. With an ever growing array of products and their complexities, manufacturing methods and customer expectations, the lot sizing problem is becoming ever more difficult to solve. Since the initial publication of Harris’ EOQ, the field of study of the lot size problem has grown tremendously and works pertaining to lot size modeling can now be classified under multiple categories. One such classification was done by Glock et al. who performed a tertiary study of existing lot size models [8]. They determined two main classification categories – a technical classification which categorized lot-sizing works based on choice of stationary or dynamic approach (see Figure 3), and content-related classification which categorizes models based on the primary features accounted for in the models (see Figure 4).
The technical classification differentiates models based on changes in the models over time – stationary versus dynamic – and application of uncertainty in the model – deterministic (no uncertainty) and stochastic (uncertainty). The content related classification differentiates the models into classical and extended. Classical models are those which share a similar structure and objective to Harris’ original EOQ model. These formulations typically focus on optimal production or order, and on inventories, setup/order and transportation costs. Extended models consider additional aspects to the lot sizing problem, including quantity discounts, scheduling, and learning curves. While this work will focus on the application of the classical model, a discussion of both types of models will be presented.
2.2.2 Lot size model review

Although classical models share a structure and objective, their complexity largely depends on the features which are accounted for in the model. In his production planning control problems, Graves considers three types of lot sizing models – linear, quadratic and mixed integer. Though the objective is the same in each model, to “determine the relative frequency of setups so as to minimize the setup and inventory costs, within the resource and service constraints of the production planning problem,” the level of model complexity largely depends on the problem framing [9]. In developing each model he considers several parameters, including type of demand, relevant costs, planning horizon, aggregate levels of products, planning decisions regarding inventory, lost sales, etc. More complex models, such as the mixed integer model, consider multiple items instead of single items, and include binary decision variables for setup, both features missing from the linear programs.

Karimi et al. also discuss the relationship between model complexity and model features [8]. Like Graves, they comment on planning horizon, relevant costs, and type of demand as important attributes. Their work focuses on a specific type of lot sizing problem, the capacitated lot sizing problem, or CLSP, its variants and solution approaches. This type of model is too complex to solve in polynomial time and is classified as NP-hard. The solution methods for an NP-hard problem such as CLSP may be classified in three main categories – exact methods,
common-sense or specialized heuristics, and mathematical programming-based heuristics. There
are several solution methods within each category, and Karimi et al. discuss a few of them, and
include a useful summary of other work papers each of which investigate one or more of the
solution methods. Karimi et al. conclude that mathematical programming-based heuristics
“usually produce better quality solutions...and allow extensions to different problems,” and have
the advantage of commercial solvers such as CPLEX or XPRESS-MP to solve the CLSP.
However they also point out that these heuristics “have much more computational complexity
for real-world problems...and cannot be easily implemented by practioners” [8].

Luss and Rosenwein also look at the capacitated lot sizing problem but through the
extended model version. They place a specific importance on the “affordability of lost capacity
due to frequent changeovers (set-ups), and the high inventory holding costs resulting from large
lot sizes” [10]. They build a model assuming different item characteristics, such as volume and
set-up time, with the objective to minimize total holding cost. The solution method utilizes a
“power of 2” heuristic programmed in FORTRAN which minimizes the total holding cost based
on the available capacity at the manufacturing facility. This heuristic chooses minimum lot size
for each item; when a capacity criteria is violated, one item's lot size is doubled, and the
computation proceeds until all items have a minimal lot size which fits into the capacity and
minimized holding cost criteria. Unlike the previous two classical models, the Luss and
Rosenwein model considers scheduling and in addition to the lot size, may also be used to
determine the manufacturing sequence of each item lot.

Drexl and Kimms investigate an extended model in the short-term domain whereby they
look at the production lot size and the sequence of the items produced [11]. They use CSLP as
the basis for their approach in deriving the discrete lot sizing and scheduling problem (DLSP),
the proportional lot sizing and scheduling problem (PSLP), and the general lot sizing and
scheduling problem. While maintaining the objective and most of the constraints identical to the
CSLP, these other extensions differ in two ways: (1) how they treat time (micro periods instead
of macro periods like in CSLP), and (2) the constraints they place on the objective function. DLSP
only schedules one item within the micro production period, leaving unused capacity if the item’s
demand is lower than available capacity. Meanwhile PSLP extends this to schedule a second item
for that unused capacity, allowing for one setup and up to two items during the same micro
production period. Finally the GSLP treats time in macro periods, much like the original CSLP,

[20]
but imposes additional constraints and user defined parameters (absent in the CSLP) which forces an assignment of each lot to a specific order in the production sequence.

2.3 Scheduling algorithms

Much like lot sizing, scheduling is a resource allocation problem which deals with allocating resources within a specified time horizon, and can also be approached using optimization solution methods. The objective functions of scheduling problems may take form of minimizing total completion time or minimizing delay of a job after its due date. Scheduling problems fall into two major categories – deterministic and stochastic, and within each there are a number of other categories based on the type and number of machines (parallel or in sequence, single or multiple, same or different speeds), type of manufacturing (batch or continuous), and the types of restrictions imposed on the items (preemptions, precedence, job families, etc.) [12]. For the case of deterministic demand and multiple parallel machines, which is the focus of this paper, Pinedo suggests several algorithms with objectives of minimal total completion time, minimal makespan or maximum lateness. Most of the scheduling problems considered are NP-hard, and much like the lot sizing problems require heuristics to achieve an optimal, or approximately optimal solution within polynomial time. Longest Processing Time (LPT) is the primary heuristic used for the objective of minimal makespan; it prioritizes item sequence based on the processing times, placing the longest timed items to produced first, followed by the next processing timed item, etc. Critical path method is secondary approach used to minimize makespan. It completes jobs at the latest possible completion time and starts jobs at the latest possible time. Any jobs which have the latest possible completion time equal to the latest possible start time are deemed critical and must be performed first. He also discusses additional heuristics, such as least flexible job first (LFJ), longest remaining processing time (LRPT), and largest number of successors first (LNS), each of which impose different constraints on the same objective. Shortest Processing Time (SPT) is the first heuristic within the minimal total completion time objective, and is followed by other heuristics similar to the minimal makespan, including critical path method and LFJ. The discussion of heuristics on deterministic demand and parallel machines scheduling problems completes with the heuristic on maximum lateness, LRPT.

Others have also approached the scheduling problem extensively. Li et al. use a similar approach to Pinedo to minimize makespan and total completion time in the application of
scheduling to a green manufacturing setting. They successfully apply LPT and SPT heuristics to the parallel machines manufacturing environment and demonstrate that these approaches work well in settings where energy efficiency is a priority and optimal scheduling is key in reducing unnecessary machine utilization [13]. Gholmai and Sotskov support Pinedo in the fact that the “high complexity of parallel machine job-shop problem [forces researchers] to use heuristic algorithms for solving” these problems in the large scale format [14]. They propose an adaptive algorithm which learns how to solve the smaller parallel machine job-shop problems, and then adapts itself to solve large scale problem of the same nature without the use of heuristics. They determined that with minimal constraints, the adaptive algorithm was effective for this type of scheduling problem when compared to other known heuristics, such as shortest processing time (SPT), shortest release time (SRT), etc. In fact, it demonstrated results closer to the optimal and with minimal computation time. However, application for more complex problem is still to be determined as the constraints, such as sequence dependent setup times, etc., have not yet been applied. The number of machines and jobs was also small, at most 10 and 20, and more work needs to be done to see how this may apply to a much larger setting.
Chapter 3

Current state of Company X

In recent years Company X has shifted its focus toward a more diverse product portfolio in order to attain its goal of enhanced customer satisfaction and new growth opportunities. While its corporate strategy looks toward the future, the company is still working to realign all of its business units toward the strategic objectives. Company X is also investigating optimization of its production planning approach within manufacturing. This chapter will take a closer look at how the company currently evaluates success within manufacturing and supply chain, and what effect unit objectives misaligned with common strategic goals have on the separate divisions as well as on the company as a whole. There will also be a discussion on the existing production planning platform and its effect on the company objectives.

3.1 Existing performance metrics

There are different performance metrics for the two parts of the company studied throughout the duration of this thesis work – manufacturing is driven by overall equipment efficiency (OEE) and conversion cost while supply chain focuses on customer service delivery. It is important to note that product quality is protected at all costs, and the aforementioned KPIs are key so long as quality is not negatively affected. There is currently poor relating of these different metrics across the divisions as each business unit works toward maximum efficiency of its own goals. This is not often desirable because some tradeoffs are necessary in order to achieve a global optimization for the entire system (the system being Company X and the global optimization
being profitability) \(^{[15]}\). In the case of Company X which is predominately driven by manufacturing, the lack of tradeoffs, specifically between manufacturing and supply chain, and the larger focus on manufacturing performance metrics is having an adverse effect on supply chain and company as a whole.

3.1.1 Manufacturing metrics of success

3.1.1.1 OEE

OEE is a key performance indicator for manufacturing in Company X. It compares current manufacturing performance, quality, availability and scheduled time to ideal conditions. There are several ways to increase OEE to the desired levels, one of which is to increase available time by reducing planned downtime such as changeovers. This increases product lot sizes and total plant output, the latter of which is a very important measure for plants – because of its ties to OEE there is a large focus at each plant to maximize total output. OEE is a valid choice for measuring manufacturing performance but it may not apply in all manufacturing situations. For example increasing plant output through minimal changeovers is acceptable in industries with large volumes and low variety product offerings. In a highly diverse product market with lower volumes, OEE may not be the best KPI measure because of its use of minimal changeovers which can reduce product variety. Company X has struggled with this particular metric as it looks to expand its product portfolio. With its current OEE definition and its traditional manufacturing system, minimal changeovers have been key to meeting OEE targets. However, to achieve its goal of better customer service and a larger market share, it needs to diversify its product portfolio. As the diversification is increasing manufacturing complexity and the strain on the production system, Company X is exploring alternative OEE measures and manufacturing approaches which can meet its goals while maintaining operational efficiency.

3.1.1.2 Conversion cost

Conversion cost is another key performance indicator in manufacturing. Lower conversion cost (and maintained product quality) increases profit margin per unit and overall company profitability. One method to achieve lower conversion cost is to produce a higher total output.
Because conversion cost is inversely proportional to total output (see Equation 1), keeping all else constant higher output will result in lower conversion cost.

\[
\text{direct labor} + \text{direct material} + \text{manufacturing overhead} \\
\hline
\text{total output}
\]

*Equation 1. Traditional product conversion cost.*

Unfortunately higher output is achieved by reducing the number of changeovers and setups which reduces the variety of products manufactured and hinders the realization of a more diverse product portfolio that is necessary to achieve the company’s goals of improved customer service and new market growth.

3.1.2 Impact of manufacturing metrics on Supply Chain

Service rate is an important performance metric for supply chain. Previous work by Karl Kulling determined that during periods of demand variability, longer lead time has an adverse effect on service level [2]. Under the existing manufacturing system, higher OEE and lower conversion cost is achieved through fewer changeovers and more total output. In a situation with a diverse portfolio, having less frequent changeovers can result in longer portfolio cycling, which further results in a longer lead time for products and consequently a lower customer service level.

A further impact of manufacturing metrics on supply chain is the focus on large lot sizes (and larger output overall). Larger lot sizes from manufacturing complicate inventory management within supply chain and create several concerns within supply chain including high inventory and opportunity costs, both of which affect the overall company profitability [15]. Higher lot size output from plants can put a strain on the supply chain which may need to store the products for longer periods of time because demand rate is slower than replenishment rate from the plant. This results in extra inventory costs for supply chain. Currently inventory cost does not factor into the product cost and product profit margin. However, high inventory cost within supply chain can impact costs elsewhere within supply chain and can have an impact on service level. If the company has higher costs in inventory storage it may need to reduce cost elsewhere, for example transportation. Reducing cost in transportation can adversely affect service level – for instance instead of air shipping a specific product to a customer, the company
will save money and ship by truck, which can increase the lead time and reduce customer satisfaction. Furthermore, long lead times and large lot sizes can create an opportunity cost for the company. If the right product isn’t available at the right time due to manufacturing considerations, this will negatively impact product availability and has a potential for a lost sale.

Similarly to many other companies Company X is not immune to differences in performance metrics affecting service level and overall profitability [16].

3.2 Production planning process

At Company X the production planning team manually creates a weekly manufacturing plan for each specific plant based on a monthly sales forecast. The main factors in the making of the production plan are available plant capacity and current inventory position of each product on the monthly ticket. The former is used to determine lot size and the number of changeovers and new setups possible within that week – this also directly relates to the number of different products which the plant is able to produce. The latter factor determines the lot size for a specific product and balances this with the available capacity.

The information on possible changeovers and setups is not uniform across different factories and depends on the number and type of machines available and the manufacturing process at each plant. Most plants operate at close to maximum capacity and there is little room for demand surges and frequent setups. In order to accommodate urgent orders the planners often do not follow the predetermined plan and manually adjust the production of less urgent products, either through removing them from the current production plan or varying the lot size. This creates a ripple effect through the rest of the production plans which require further manual adjustment. The consequence of these manual adjustments are non-value added time for the planner to manually redo all future forecasts, and delay in manufacturing some products which ultimately affects the customer service level. There have been previous attempts at automating the process of determining the optimal lot size and cycling of each product; however the models created for this task were complex and are not widely used within the company. There is no uniform method across the company to determine the lot size and cycling of each product, and each region has its own spreadsheets and heuristics for production planning.
Finally, at the plant level, scheduling of production to machines is not automated and requires the manual manipulation from the operator. This is a tedious and very time consuming task which has no guarantee of optimal scheduling.

3.3 Summary

This chapter discussed the existing misaligned objectives between manufacturing and supply chain and the impact this has on each business unit as well as the company’s strategic goals. Manufacturing focus on increasing output in order to lower manufacturing cost and to improve operational efficiency puts a strain on supply chain, which struggles to keep up with the large product volumes and deliver the right product at the right time to the customer.

In addition to misaligned objectives, production planning within manufacturing is also not optimized toward attaining the company’s strategic goals. Currently the planning process is very manual and frequent manual manipulations of lot sizes and product cycling do little to guarantee customer service level improvement. Furthermore, the manual scheduling process creates much non-value added time during the planning phase within the manufacturing facility, and does not guarantee optimal results.
Chapter 4

Production allocation decision framework

Some of the challenges which Company X faces may be mitigated by an integrated production and supply chain network design and manufacturing differentiation. The company is currently looking at several proposed manufacturing systems and assumes a “one size fits all”, a “one correct answer” solution. This chapter will evaluate two of these systems under an integrated production and supply chain network design. We will consider the system network end to end and propose a way to align the business units toward common strategic goals for the company, which are to improve service level and to expand growth in new and existing markets. Furthermore, we will examine how the use of differentiated manufacturing channels will better enable the company as a whole to move toward achieving said strategic goals.

4.1 Theory

Company X is currently examining several alternative manufacturing systems for product manufacturing. Our efforts are focused on systems A and B and we will discuss production allocation decision making between these two systems. We will examine the cost differences, production flexibility and capacity availability in both systems to determine if one is inherently “better” than the other, or if there exists a possibility of utilizing both systems in a manufacturing differentiation strategy. In this section we will present the theory behind our decision making framework.
4.1.1 Total delivered cost

Knowing the true product cost is an important strategic advantage in any industry. It allows a company to better price its products and potentially enjoy a better profit margin when compared to its competitors. Company X, a manufacturing driven business, considers true product cost to be conversion cost, writing off any incurred inventory cost as a supply chain expense and therefore not attributable to the product. This is misleading because what follows is a series of operational decisions which ultimately negatively impact the company objectives of better service level and new market growth. This analysis proposes a new performance metric, total delivered cost, and compares it against conversion cost (the existing metric) to determine the impact that using total delivered cost has on operational decisions. This analysis considers total delivered cost to include product conversion cost and product holding cost. When we discuss conversion cost, we also propose an alternative method for its calculation. The comparison is done through two manufacturing systems both of which can be integrated into network design – system A and system B.

4.1.1.1 Conversion cost

In the standard costing method which Company X currently uses, the conversion cost is assumed to be the same for all products manufactured in the same facility. Cost per unit is a function of total output and total costs resulting in an average cost per unit (both direct and indirect). Our analysis looks at a cost per unit on a SKU level to determine if the cost can really be averaged for all output or if there are differences between SKUs. Specifically we isolated setup cost to understand if setup time and lot size affect the conversion cost per unit. When comparing the conversion cost of the two systems, the cost is normalized against system size and indirect costs which bear no effect on the final production cost. Only direct manufacturing costs are attributed to the final conversion cost in both systems; these include labor, equipment and facilities. Raw material cost is excluded from this analysis because it is assumed to be the same in each system. By using the direct costing method we can better isolate which factors have an effect on the conversion cost.

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1 For a deeper discussion on this topic please see Chapter 3 which discusses the limitations of this existing point of view.
Cost per unit = \( \frac{C_p \times (P \times L) + C_s \times S}{L} \)

Equation 2. Cost per unit formulation. The cost per unit is calculated based on the cost per hour for the facility, which is based on all direct costs such as equipment, labor and facility costs. Time measured includes the total production time and the setup time, both of which are variable with lot size.

\begin{align*}
C_p &= \text{production cost per unit time} \quad [\$/\text{hr}] \\
C_s &= \text{setup cost per unit time} \quad [\$/\text{hr}] \\
P &= \text{production rate} \quad [\text{hr/unit}] \\
L &= \text{lot size of product } i \quad [\text{units}] \\
S &= \text{setup time for product } i \quad [\text{hr}] \\
\end{align*}

In the conventional method the conversion cost is affected by the total output and the sum of all direct and indirect costs. It is difficult to isolate which factor has an effect on the final conversion cost. Let's take a lot size of 1,000 units – does the cost differ between making one lot of 1,000 units or making 10 different lots of 100 units each? In the case of the current conversion cost there is no difference. In this analysis we compute that cost is proportional to setup cost and lot size. We base the cost on cost per unit time, which is derived from all direct costs such as labor, equipment and facilities. Equation 2 summarizes the relationship between lot size, setup time, production time and cost. The time is derived from production and setup time. Setup time can be affected by the lot size due to machine capacity (more machines may be required for a larger lot size, and hence a larger setup time) and by the manufacturing complexity of each SKU. Our analysis focuses on the former. The production capacity is assumed to be constant in both manufacturing systems, with multiple SKUs produced in each system at the same time. We isolate the cost of each SKU produced and observe how the production cost is affected in each system because of the setup and lot size.

4.1.1.2 Inventory cost

At Company X inventory cost is attributed primarily to four factors – (1) storage, (2) cost of capital, (3) obsolescence, and (4) long term storage. Storage refers to the regular warehouses where product is kept until it is shipped to the customer. Cost of capital refers to the opportunity
cost of paying for storage instead of using the money elsewhere. This is taken as the rate of return internal for the company. Obsolescence is the inventory which must be written off because it had not been sold within a specified time. Finally long term storage refers to the storage spaces additional to the regular warehouses; this space is predominantly used for storing products which have a long cycle or for which demand was overestimated and lot size overproduced so there is no space in the regular warehouse. Long term storage is not always located close to the plant or warehouse and requires additional logistics cost. In our study only inventory cost attributed to factors one and two are considered. This is because the information to determine factors three and four is not readily available for the products in the analysis, and our analysis would have been incomplete if only partial information was used. Hence the decision was made not to include obsolescence and long term inventory in the holding cost analysis.

The storage cost portions of the computation includes the cost of storing the safety stock and a portion of the lot size for the entire production cycle; this cost is specific to each SKU because it depends on the annual demand and chosen lot size which are unique to each product SKU. Given the same annual demand, a higher lot size will result in higher storage costs because the product will spend longer in storage than will a small lot size due to the difference in production frequency and safety stock. The production cycle for system A is based on a level design which is specific to each region and determines production frequency based on annual volume for each product\(^2\). The production cycle is defined as the time (typically days) between replenishment of the lot size. It determines the frequency of production per year – that is how many times a year the particular product is made. For example, if the production cycle is 10 days, the lot size of SKU 123 will be made every 10 days. The lot size may take several days to manufacture but a new lot size will not be manufactured until 10 days after the start of the previous lot size. If the demand is larger than expected and the units run out day 5 into the cycle, a new lot size will not be made until 10 days have passed since the start of the last replenishment. Manufacturing every 10 days will result in a frequency of approximately 36 times per year. The frequency per year, in addition to plant capacity and operational efficiency, help to define the level design. The level design is a used to classify products into categories to determine how often a product should be manufactured within the year. The levels are determined based on total annual demand – higher demand products are produced more often throughout the year while lower demand products are produced less frequently throughout the year. A sample level design matrix

\(^2\) The level design used in this study was specific to European plants as this was the most readily available data.
is shown in Table 1. If a SKU has an annual demand of at least 200,000 units (level design \( \alpha \)), its stock will be replenished (it will be produced) approximately 8 times a year, or roughly every 45 days. If a SKU demand falls anywhere between 1 and 10,000 units per year, all of its units will be manufactured once a year (level design \( \sigma \)).

<table>
<thead>
<tr>
<th>Level Design</th>
<th>Minimum Demand</th>
<th>Frequency per year</th>
<th>Production period (days)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \alpha )</td>
<td>200,000</td>
<td>8</td>
<td>45</td>
</tr>
<tr>
<td>( \beta )</td>
<td>60,000</td>
<td>5</td>
<td>75</td>
</tr>
<tr>
<td>( \lambda )</td>
<td>10,000</td>
<td>4</td>
<td>100</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>1</td>
<td>1</td>
<td>365</td>
</tr>
</tbody>
</table>

Table 1. Sample level design

Given two different annual volumes, for example those that fall under level designs \( \lambda \) and \( \sigma \), the production frequency in system A is variable, either 4 or 1 times a year, while the daily lot size is assumed to be approximately constant. Contrary to system A, the production frequency in system B is not fixed based on the annual volume. There is more flexibility in order to accommodate for more granular demand variation with regards to time, thereby allowing a lower safety stock and lot size between cycles. Both the daily lot size and the production frequency can be adjusted in response to demand as needed.

The safety stock is computed based on Equation 3. We assume that safety stock is used to mitigate demand variability and lead time variation is very little (and hence omitted).

\[
SS = z_a \sqrt{E(L) \sigma_D^2 + E(D)^2 \sigma_L^2} \approx z_a \sigma_D \sqrt{E(L)}
\]

Equation 3. Safety stock

\( SS \) = safety stock
\( z_a \) = z-score (assume \( a = 90\% \), \( z_a = 1.28 \))
\( E(L) \) = mean lead + cycle time
\( E(D) \) = mean demand

---

\(^3\) Introduction to Operations, 15.761, Summary 2014
$\sigma_D =$ standard deviation of demand

$\sigma_L =$ standard deviation of lead time (assume 0)

The safety stock computation was the same for both system A and system B – both demand and service level were treated as equal. System A necessitated a higher safety stock, however, due to the longer average lead time as a result of longer production cycles.

4.2 Results

In this section we will present our findings with regards to our analysis of total delivered cost in the two different systems studied. We will also evaluate other parameters such as system responsiveness, lead time, and flexibility, and present a qualitative observation regarding advantages of channel differentiation in the manufacturing sector.

4.2.1 Total Delivered Cost

The total delivered cost is the combination of production and inventory costs for each SKU. We will first look at each cost separately to understand their behavior independently and to observe any conclusions with regards to operational decisions. Finally we will look at the effect of the total delivered cost on the operational decision of how to manufacture a product.

Figure 5 plots the computed conversion costs for systems A and B versus lot size, and the conversion cost of systems A and B computed using the traditional costing method. We can observe that the isolation of setup and lot size results in a much different cost per unit under the new model than under the current method which ignores both. It is important to note that there is also a big difference between the two systems with regards to setup time. Setup time is a significantly larger proportion of the total production time in system A than in system B, and consequently a larger proportion of the conversion cost; this is due to fundamental differences in the manufacturing process. As a result of this in system A setup is a significant part of the cost and has a large effect on the conversion cost at lower lot sizes. At larger lot sizes economies of scale dominates and setup cost becomes less significant. Meanwhile in system B, where setup is not as large a part of production time as in system A, the setup cost does not have the same profound effect on cost.
Figure 5. Production cost per unit versus lot size. Assumptions – system capacity is constant in both systems, production is over 7 consecutive days, same product on both systems with the same annual demand.

Two important conclusions can be drawn from this analysis – (1) setup and lot size have a significant effect on the conversion cost per unit, and (2) ignoring these effects, looking only at the average conversion cost will incorrectly point the company toward the direction of producing all products in system A and in large lot sizes. Point 1 suggests that at least from the perspective of conversion cost, there should be two separate manufacturing systems depending on the preferred product mix (based on annual volume). Conclusion number 2 suggests that if the cost per unit is the same regardless of lot size, then larger lot sizes should be manufactured – and only in system A – in order to maintain high operational efficiency. This directly contradicts the strategy of higher product differentiation and improved service level. The point of higher product differentiation will be addressed in Section 4.2.2, while the latter was already address in a previous MIT thesis [2] which determined that larger production cycles [due to larger lot sizes] result in lower service level. The second point also leads us into the next discussion point, inventory cost.

Figure 6 represents the inventory cost per unit as a function of annual volume. Note that this carrying cost highly depends on the lot size; in this case an approximate lot size representative of each system is used, $a$ and $b$ units for system A and system B, respectively.
These lot sizes are chosen because based on Figure 5 at a lot size of $a$ and $b$ the conversion cost for each system (using the proposed computation method) is at its cheapest (hence this lot size is a likely scenario). For simplicity of graphing the same lot size is used for all of the annual demand in Figure 6. For optimal results, the lot size should vary according to the annual demand.

The smaller lot size of $b$ is also determined to be appropriate as some SKUs are projected to be produced in a low amount; since system $A$ is not cost efficient at producing them, our analysis focuses on the inventory cost differences for a SKU which needs such a small lot size that is offered by system $B$. In general, as the lot size becomes larger, the carrying cost per unit for both systems increases as there is more product stored in inventory. In Figure 6 we kept the lot size the same and we can observe that as the annual demand volume decreases the inventory cost for both systems increases because production during a cycle is more than demand in that cycle, so
some lot sizes remain in inventory longer than if the demand matched or is higher than production amount during the same time period. Notice also there is a sudden drop in cost at point X due to the switch in the level design policy in system A. Any time the demand shifts from level design A to B, etc. there is a longer production cycle, which consequently requires a larger safety stock and higher inventory. Notice that since the lot size in system A is larger than that in system B the resulting holding cost per unit is much larger in system A than B for the same annual demand volume.

Figure 7 shows the combined total delivered cost for systems A and B, with the inventory cost from Figure 6 and the conversion cost from Figure 5 based on the chosen lot size.

![Total delivered cost per unit](image)

**Figure 7.** Total deliver cost for systems A and B; includes conversion cost and inventory cost.

We can observe that for products with lower annual demand, the total delivered cost for system B is lower than that for system A. If we recall, this agrees with earlier conclusions for both inventory and production costs calculated independently – lower annual demand results in lower costs in system B. We can observe that at higher annual demands, production cost in system A is lower than that in system B and this mitigates the total cost despite the fact that inventory cost in A is still higher than in B. As a result, we see that at higher annual volumes the gap in
The result from Figure 7 is very significant because it highlights the fact that conversion cost alone is not the best metric for determining whether the product cost is optimized. If only conversion cost had been used in this decision, then system A would have been chosen for all SKU production, from lower to higher annual volumes. However, that would not have been the best position because it would have resulted in higher overall product cost due to higher inventory cost at lower demand volumes. Consequently the product price and product margin would have been affected. However, based on the performed analysis using the total delivered cost, it is clear that system A is more cost effective to manufacture products with larger annual volumes while system B is more suited to produce lower demand volume products.

4.2.2 Product variety as a function of capacity

There are other benefits to looking at total delivered cost as a performance metric. If we proceed to manufacture low volume products in system B and high volume products in system A, we can also observe what effect this decision will have on the overall company goal – improve service level and market expansion through product proliferation. The former point was addressed in a previous thesis [2], while the latter point is addressed below.

An additional factor to consider in determining if and when each manufacturing system should be used is the consideration of product variety. Remember that system A is strongly affected by new setups when it comes to conversion cost while system B is minimally affected by new setups (refer to Figure 5). Now we will look at how low lot sizes and new setups compare in each of the two systems. Table 2 shows the numbers of SKUs that are possible to manufacture under each manufacturing system given a specific lot size and over the same time frame of 7 days and an equal product capacity in each manufacturing system. We can see that at lower lot sizes system B dominates in the number of SKUs it can manufacture. However, under a higher lot size both systems produce a low number of SKU.
4.2.3 Differentiated Manufacturing Channels

A previous LGO project demonstrated that there exists greater product variety within SKUs of lower annual demand, and less product variety within SKUs of greater annual demand [2]. Combining the results of this project with the results of the previous LGO project we demonstrate the need for a differentiated channel manufacturing strategy. Lower annual demand products which have greater SKU variety display the need for system B which is able to manufacture lower lot sizes at less cost and with greater variety availability than system A. Higher volume demand products display the need for system A which is able to produce large lot sizes at a lower cost and does not have the unnecessary flexibility to provide multiple product types.

Figure 8. Strategic Efficient Frontier.

[38]
An additional benefit to the integrated production and supply chain system and the differentiated manufacturing strategy is the ability to create more value for the consumer through the improvement of the responsiveness of the system. This value creation repositions the company in a more strategic position within the competitive landscape [18]. Currently Company X has a low responsiveness on some of its products toward its customers and a low cost for manufacturing. This may seem to put them at an advantage because they are on the efficient frontier at point A (see Figure 8). However, their total delivered cost is higher than it appears (due to aforementioned inventory costs) and therefore there are not actually on the efficient frontier but away from it at point B. Through this integrated and differentiated strategy Company X will be able to not only move up the efficient frontier and create a new position and a new frontier, but it will also be able to capture a wider position, between points C and D, by running an integrated and differentiated system that will enable Company X to capture the low responsiveness and low total delivered cost market as well as the high responsiveness and low (maybe slightly higher) total delivered cost market. Hence, it will profit from being more responsive to the customer when it needs to be and growing its market, both within its corporate strategy.

4.2.4 Addressing market growth through differentiated sales channels

This result also addresses the company’s goal at expanding market growth. By being able to provide a greater product variety, the company will be able to enter new markets which it previously could not because it did not manufacture the appropriate products. Whereas before it could not offer a wide selection of low volume products, the case for having two manufacturing systems allows it to focus on both high and low volume SKUs. This will be useful in markets where the company is looking to expand its market share. It would also be useful in markets which have differentiated retail options; for example – (1) big chains with lots of storage capacity (require large lot sizes of a limited range of products), (2) mid-size stores which can handle larger lot sizes but have a larger variety of products than (1), and (3) small footprint stores which have limited storage capacity but require a large product selection (small lot sizes of many different products). Thus far Company X has had a difficult time expanding sales with customer types (2) and (3). However, as the footprint of these customers grows globally, Company X needs to better serve them in order to gain more market share. Hence, distinguishing between the two different
types of manufacturing systems is critical – by refocusing production of large lots (customer (1)) in system A, the company is able to better serve customer (1) while maintaining its operational efficiencies in its factories. And by shifting focus of lower production volumes to system B, it is able to address the needs of customers (2) and (3) which require smaller volumes and greater variety. Finally, it will be able to maintain low total delivered cost for each type of product and thus maintain a competitive advantage.

4.2.5 Lead time improvement

Previous thesis done by MIT’s Karl Kulling suggests that a faster lead time will lead to higher customer service. Faster lead time is especially necessary for low volume products since safety stock level is not as high as in large volume products, which requires a faster replenishment time. We have already determined that system B is best for low volume products due to lower cost and greater product variety than system A, which is optimized for larger volume products. Another dimension which supports this conclusion is the lead time of a product in each type of manufacturing system. A value stream analysis was performed to determine value added and non-value added time in each system. The boundary around the analysis was the planning cycle and the manufacturing cycle, stage I and stage II, respectively. The analysis considers cycle time of one product through the system. System A planning cycle is approximately 5 times larger than

![Figure 9. Summary of value stream map for system A and system B. Overall, system B was faster than System A between 4 to 6 times.](image)

the planning cycle in system B. The manufacturing time (value added time) of the product within each system is approximately equivalent. Figure 9 show the summary of the value stream map analysis which was performed on each system. System B is 4 to 6 times more responsive than
system A with regards to lead time. This large difference stems from a greater NVA within the manufacturing facility (primarily due to a much larger WIP within system A) and the difference in the planning cycles. Non-value added (NVA) time is considered to be any time which does not add more value to the product for the customer. For example, the value of product XYZ is the same to the customer regardless of whether it took 1 day or 40 days to plan for the production of that item. However, there is value added in the manufacturing process which is the time where the product is differentiated between other products. Likewise, any WIP is also considered NVA since that also does not increase the value of the product to the customer.

Note also that the difference in lead time for both systems once more supports the case for a differentiated manufacturing channels strategy discussed earlier. The result demonstrates a shorter lead time for system B which, based on previous results, again suggests that system B is a better fit for lower volume products. This is because lower volume products require a smaller lot size (to minimize total delivered cost) and thus a faster replenishment time. If the replenishment time was as slow as in system A, then a larger safety stock would be needed, which would then increase the total delivered cost to Company X. One might consider why, based on this result, not use system B for larger volume products also. The primary reason is that because larger volume products already require large volumes, they will have a larger safety stock, enough to cover the longer lead time. Also, because the demand for these products is less variable than the demand for lower volume products [2], having a longer lead time is less of an issue because an appropriate amount of inventory is easier to forecast. As we have seen already, larger inventory for these products also doesn't necessarily result in higher total delivered cost because there is large enough demand to balance the larger inventory stock. Because the demand is steady, we can expect 9,000 units to be gone within a month, whereas we cannot guarantee the same for 9,000 units of a lower volume product whose monthly demand is lower and less stable. Hence, system A does make sense for larger volume products even though it has a higher lead time. With that being said, though, there should certainly be an outlook to improve operations and reduce lead time in order to get better service level. The analysis did determine that there can be significant reductions in WIP in system A, which would decrease the total lead time by as much as 10%.
4.3 Summary

This chapter examined an integrated production and supply chain network and a manufacturing differentiation strategy. We proposed a new performance metric for success, total delivered cost per product, and demonstrated how this proposed metric supports the case for differentiated manufacturing with respect to system A and B. Using the previous performance metric, only system A would have been used to manufacture all products. This would have continued the current trend of an overflowing supply chain, low product proliferation and low service levels. However, the implementation of the new metric which integrates manufacturing and supply chain principles highlights the need for two separate production systems – one for larger volume products and a separate one for lower volume products. By separating the production, Company X is able to lower total delivered cost, provide a greater product variety and reduce lead time to its customers. The projected results also demonstrate that the new metric will better enable the company to align its business units with the overall company strategy to offer a diverse product portfolio and expand its growth into new and within existing markets.
Chapter 5

Optimized production planning

Currently there is no uniform, optimized method to determine the manufacturing lot size at Company X. Each region has its own production planning team which decides on the lot size based on the region's modus operandi, for example inventory position or minimum manufacturing lot size. The team is often constrained by manufacturing and in recent years, as the product portfolio has grown, it has struggled cycling lower volume products due to those constraints. Previous analysis in this thesis already determined the need for separate volume based manufacturing systems. This additional analysis is focused on system B specifically, and examines lot size determination alternatives to the current methods used within Company X. Furthermore, we will examine optimization with regards to scheduling products on specific machines. Currently this is done manually, and in addition to non-value added time for the operator does not guarantee an optimal schedule.

5.1 Theory

5.1.1 Scheduling optimization

The existing scheduling of product to machine in the final stage of production is done all in manual mode. Each plant has its own scheduler who uses past experience and self-developed heuristics to determine the sequence of products on a specific machine. We examined several
different optimization algorithms for automating this step in the production process. Our assumptions included a multi-item, parallel and identical machine environment with deterministic demand. All data, such as processing time and demand, is known ahead of time, thus this is considered an offline scheduling problem. There are several different types of objective functions which can be considered, such as minimizing completion time or reducing tardiness or lateness. Since we did not have specific “due dates” for the products to be manufactured, we focused on minimizing the completion time. Within this category, we focused on two specific types of objective functions – minimizing makespan and minimizing average weighted completion time (or flow time). The makespan is “equivalent to the completion time of the last job to leave the system” (see Equation 4) whereas average weighted completion time seeks to minimize the average flow time of each job \([12]\). Both are NP hard problems and require heuristics in order determine a solution.

\[
\text{Makespan} = \text{Time of completion of last job} - \text{Starting time of the first job} \quad [19]
\]

\[
\text{Average weighted completion time} = \text{finish time} + \text{time since job arrived at workstation} \quad [19]
\]

Equation 4. Makespan and Average weighted completion time.

The suggested heuristic to use for minimizing the makespan is the Longest Processing Time (LPT) rule which processes the longest jobs first, followed by shorter jobs \([12]\). This allows for minimizing machine idleness and using shorter jobs at the end of the schedule to balance the machine loads. While it is not 100% optimal, this heuristic is close to \(4/3\) of the optimal schedule. More specifically,

\[
\frac{C_{\text{max}}(LPT)}{C_{\text{max}}(OPT)} \leq \frac{4}{3} - \frac{1}{3\times m}
\]

Equation 5. For parallel machine with no priorities, LPT is approximately \(4/3\) optimal of the optimal schedule \([12]\)

\(C_{\text{max}}(LPT) = \text{makespan of LPT}\)
\(C_{\text{max}}(OPT) = \text{makespan of OPT}\)
\(m = \text{number of parallel machines}\)

This heuristic was programmed into the Python language using inputs of the number of machines available, the number of hours available, and the processing times of each product. The
output results in each lot being assigned to a single machine. If there is excess capacity on the machine, the next largest lot which is able to fit within the capacity is assigned to the same machine.

A heuristic was also used for minimizing average weighted completion time; the suggested heuristic is Shortest Processing Time (SPT) which processes shortest jobs first, followed by the next longest job. This heuristic is considered to be optimal for minimizing average weighted completion time \([12]\). By positioning the shortest jobs first the average flow time is minimized because we are minimizing the delay of the each job. This heuristic was also programmed into Python language with the same inputs and outputs as LPT. The major difference is that this algorithm arranged the processing time in increasing order while LPT rearranged the time in decreasing order.

5.1.2 Lot size optimization

We examined several different lot size algorithms for application in system B. From conversations with manufacturing, supply chain and production planning teams we determined that there are several important criteria in lot size determination, including capacity constraint, inclusion of inventory, setup and production costs, and a flexible time variable. The objective function for all the algorithms is to minimize total delivered cost, which includes inventory, setup and production costs. A capacity constraint is also included because when scheduling a ticket of products, it is important to ensure that the combination of the lot sizes is within the limits of available capacity, otherwise some products will not be able to be manufactured. Finally, we wanted to be able to vary the time frame for the algorithm; products for system B have some demand variability and we want the algorithm to have flexibility so the production plan could be revised if changes occur. Table 3 compares the lot size optimization functions we examined based on the selected criteria. We chose the current algorithm to be a lot size based on inventory position and manufacturing capacity limitation. It only considers capacity limitations and does not adjust for flexible time or any of the three costs. Next we looked at EOQ, the standard lot size optimization method in operations. We also adjusted EOQ to EOQ* which accounts for manufacturing capacity limitations \([20]\). Both EOQ and EOQ* were implemented using Excel while the final method studied, mixed integer program (MIP), was implemented using a code written in Python language.
Table 3. Summary of various criteria accounted for in different lot size algorithms.

<table>
<thead>
<tr>
<th></th>
<th>Flexible Time</th>
<th>Inventory cost</th>
<th>Setup cost</th>
<th>Production cost</th>
<th>Capacity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Current</td>
<td>+</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>EOQ</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>EOQ*</td>
<td>-</td>
<td>+</td>
<td>+</td>
<td>-</td>
<td>+</td>
</tr>
<tr>
<td>Mixed Integer</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
<td>+</td>
</tr>
</tbody>
</table>

5.1.2.1 *Economic Order Quantity (EOQ) and EOQ*

The standard EOQ formulation, presented as Equation 6, is considered due to the fact that it optimizes on the holding and setup costs; it is the simplest of all the algorithms examined. This approach examines an annual horizon and assumes that all costs and demand are constant through the year. Furthermore it assumes unconstrained capacity and is therefore not ideal in an environment which is affected by capacity constraints. An extension of this algorithm is examined, and includes a Lagrange multiplier factor, $\lambda$, which accounts for manufacturing capacity limitations ([20], [21]). The EOQ* extension is presented as Equation 7. The Lagrange multiplier is common to all items, $i$, and it is a multiplier of the setup cost. Effectively $\lambda$ is a shadow price on setup time and represents the implicit cost of time [20]4. The cycle time and all costs of each product are assumed to be fixed, as in the standard EOQ formulation. The lot size and $\lambda$ factor are dynamically varied as more products are added to the system until maximum capacity is reached. When final capacity is reached, based on the sum of all annual demand against available capacity, the lot size for each product is resolved. Like in the standard EOQ formulation, however, the planning horizon is annual and all demand and costs are assumed to stay constant. As noted earlier most of the lower volume products are not 100% predictable in their demand, hence planning for a fixed lot size for an entire year when demand might change halfway through is risky and not entirely cost effective. An additional concern with both EOQ and EOQ* is that scheduling their lot sizes to machines required a significant amount of manual work. This lot size algorithm falls under the classical models (as noted in Chapter 2) and does not automatically create a scheduling sequence for each lot size and product on the available machines.

---

\[ Q = \sqrt{\frac{2 \times D \times F}{h}} \]

*Equation 6. EOQ lot size.*

\[ Q^*_i = \sqrt{\frac{2 \times D \times \Lambda \times F}{h}} \]

*Equation 7. EOQ* lot size.

\[ D = \text{annual demand [units]} \]
\[ F = \text{fixed setup cost [$/setup]} \]
\[ h = \text{annual holding cost [$/unit]} \]
\[ Q = \text{lot size} \]
\[ \Lambda = \text{Lagrange multiplier} \]

Because both EOQ and its extension are based on an annual time period, in addition to lot size the number of total lots is also computed (to ensure demand is met). The number of manufacturing lots for each SKU is not the same as the next SKU, so in addition to scheduling the lots to machines, we also had to manually determine the cycling for each SKU based on the number of lots and schedule which week each lot would be produced. Since a multi-period scheduling optimization was not the focus of this research, the latter task had to be done manually, defeating the purpose of automating lot scheduling. This will be discussed further in section 5.2.

5.1.2.2 Mixed Integer Program

Both EOQ and EOQ* are adequate algorithms for lot size determination – they both consider cost, and EOQ* considers capacity. However, most planning is typically done on a rolling basis, hence an algorithm which has greater flexibility with the time constraint is ideal because it will allow us to revise the plan as new information on demand and production is obtained, and thereby be more flexible to customer needs. A mixed integer algorithm provides us with this greater
flexibility as it includes a production time variable in addition to minimizing total delivered cost and being capacity constrained. The MIP formulation examined follows the EOQ objective and “determines the relative frequency of setups so as to minimize the setup and inventory costs, within the resource and service constraints of the production-planning problem” \cite{9} (see Equation 8); it also adds a time dimension which EOQ disregards. Like EOQ, however, it does not account for safety stock and the inventory term is only the inventory resulting from the lot size required to meet demand during that period. In other words, if the planning period is 7 days with demand 700 for one product, due to capacity restrictions the MIP may suggest producing two lots of 350 units each. Assuming the daily demand is 100, a lot size of 350 would mean an inventory of 250 until the next lot is produced within that period.

\[
\sum_{t=1}^{T} \sum_{i=1}^{I} c_{pi} p_{it} + c_{qit} q_{it} + c_{yit} y_{it} \\
\text{Equation 8. MIP for lot size determination.}
\]

\[s.t.
q_{it} - q_{i,t-1} + p_{it} = d_{it} \quad \forall i, t \ [2]
\]
\[
\sum_{i=1}^{I} a_{i1} p_{it} + a_{i2} p_{it} \leq b_{t} \quad \forall t \ [3]
\]
\[
p_{it}, q_{it} \geq 0, y_{i} = 0,1 \quad \forall i, t \ [4]
\]
\[
p_{it} \leq B * y_{it} \quad \forall i, t \ [5]
\]

\(c_{pi}\) = unit variable cost of production for item i in time period t
\(p_{it}\) = production of item i during time period t
\(c_{qit}\) = unit cost of inventory for time i in time period t
\(q_{it}\) = inventory of item i at the end of time period t
\(c_{yit}\) = setup cost for production of item i in time period t
\(a_{ik}\) = amount of resource k required for production of item i
\(y_{it}\) = binary decision variable to denote setup of i in time period t
\(b_{t}\) = amount of resource available in period t
\(B\) = a large constant
The MIP is much more flexible with the time constraint than EOQ/EOQ* and allows us to examine production scheduling cycling outside of the one year mark. If we know demand for two weeks in advance, we can run the algorithm to determine how many setups each SKU requires in order to meet demand while minimizing total cost. If the next two weeks after that the demand profile changes, we can recompute the new lot sizes for that production cycle while still minimizing cost and staying within capacity limits. This is a huge difference with EOQ/EOQ* which determine the exact lot size and number of lots to be run within that year. This is also different from the current situation where lot sizes are determined based on the inventory position and without any regard to the cost. Since only demand within the time period studied is accounted for, the scheduling is constrained to that specific time period and there is no need for multi-period scheduling. Thus, we are able to implement the scheduling algorithms studied and reduce the NVA due to manual scheduling. The results will be presented and discussed further in section 5.2.

Despite the many benefits to using MIP, there are two downsides – one is that like the previous algorithms it falls under the classical models classification and does not automatically schedule the lot sizes to available machines; hence a secondary scheduling algorithm is required. A second major limitation is its need for a professional solver license. The written Python code for this MIP used open source license for computation, which severely limited the computing power. When we simulated 84 products over 7 days, the number of constraints became more than 1,000 and this resulted in more than a 16 hour computation using an open source license. A similar computation done on a professional solver would have taken less than 10 seconds. Unfortunately this license was not available at the time of this research study, which severely limited our ability to perform sensitivity analysis with number of products and number of days. Our results are limited to running the model for a range of 33 to 84 products over a period of 7 days. Despite the limitations in the sensitivity analysis, the results obtained are still satisfactory and make the case that if the solver license hurdle can be overcome, this is a promising algorithm for lot size determination. More on this is discussed in the next section.

[49]
5.2 Results

The lot size and the scheduling algorithms are studied together to determine the feasibility of both to be used in one production system. We looked at a specific portfolio of products which would be manufactured under one production ticket. We calculated the lot size under each lot size algorithm and then used the scheduling algorithms to schedule the lot sizes to the available machines. Machine capacity is based on total available hours within the production cycle less the predetermined downtime for maintenance. Capacity at each machine further decreases with each additional new product setup. Given the same cost and demand assumptions, EOQ and EOQ* computed higher product lot sizes than MIP. Larger lot sizes resulted in both longer production time at each machine and a larger number of machines being used. The capacity of each machine is $c$ products per day (given the cycle time of $t$ for each product and total available capacity $C$). If the lot size is larger than $c$ times the number of days in the production cycle, then a second machine must be used to produce the lot size. Hence the larger lot sizes computed by EOQ/EOQ* required more machines than the smaller lot sizes computed by MIP. Since the number of machines is fixed, when all the machines are used there is no possibility to add more and if not all products were able to get on the machines in that cycle, then not all products on the ticket will be produced. The combination of EOQ/EOQ* and the scheduling algorithms used did not result in 100% production ticket compliancy, meaning that not all the products were able to be scheduled. In contrast, the MIP and LPT algorithm resulted in 100% ticket compliancy. The MIP and SPT algorithm also did not produce all of the products on the ticket. The differences between the EOQ and MIP are clearly observed in Figure 10 and Figure 11 which display the Gantt charts for each combination of lot size and LPT scheduling algorithms. The larger lot sizes due to EOQ end up using more machines that the smaller lot sizes derived from MIP. Furthermore, there is more utilization at each machine with MIP than EOQ (under the same assumptions for scheduled maintenance downtime depicted as “safety”).

[50]
The Gantt chart analysis performed looked at the specific production cycle time which was used as an input into the MIP equation. With MIP, the lot size is computed based on the chosen production time period. Assuming the same deterministic demand each production cycle for the
entire year, and equally sized production cycles, the Gantt chart will remain the same each cycle for MIP, making it easier to know spare production capacity availability. When EOQ/EOQ* compute the lot size, there is no set variable for the production cycle — in other words even though demand is also treated as deterministic (as was assumed with MIP) the number of production cycles cannot be specified and instead it is computed based on the lot size. Hence, the number of cycles is not uniform for products and depends on the annual volume. As a result the utilization of each machine is not uniform each cycle — some weeks the resulting Gantt might be the same one as in Figure 10, whereas other weeks more machines could be used while still other weeks less machines could be used. This is not an ideal result because it makes it hard to predict spare capacity and requires more manual adjustment to scheduling (since lot sizes cannot all be produced in one cycle at times, the planner will have to manually adjust when the missed products can be put into production without creating additional capacity issues in the future).

An additional analysis was done to determine the final total inventory, setup and production costs under each lot size and scheduling algorithms combination. The results of one such combination, LPT and EOQ and LPT and MIP, are presented in Table 1. As a result of larger lot sizes not all of the ticket was scheduled and EOQ resulted in only 85% ticket compliancy whereas MIP method the entire ticket was scheduled and produced. Furthermore, the larger lot sizes resulted in larger inventory costs and larger setup costs (the latter due to a larger number of machines being used for each lot size). Finally, because not all of the ticket was scheduled to be produced, we assumed those that were not scheduled as lost sales, which is reflected in the revenues.

<table>
<thead>
<tr>
<th>Lot Size Method</th>
<th>Products on Ticket</th>
<th>Weekly Ticket Compliancy</th>
<th>Annual Inventory Cost</th>
<th>Annual Setup cost</th>
<th>Weekly Revenues (SX average price)</th>
</tr>
</thead>
<tbody>
<tr>
<td>EOQ</td>
<td>33</td>
<td>85%</td>
<td>+++</td>
<td>++</td>
<td>+++</td>
</tr>
<tr>
<td>MIP</td>
<td>33</td>
<td>100%</td>
<td>+++</td>
<td>+</td>
<td>+++</td>
</tr>
</tbody>
</table>

We assume the plant runs on uniform cycles even though EOQ doesn’t compute the same number of cycles as the plant might run on.
Finally, a sensitivity analysis was performed on inventory and production costs. As expected with EOQ/EOQ*, higher inventory costs results in higher total inventory costs and also higher production costs. The production costs are higher because setup cost is a part of the production cost per unit – higher inventory results in smaller lot sizes but also more setups per year which in effect increase the production cost per unit and the total production cost. The opposite effect occurred when inventory costs were decreased. When production costs were increased there was a slight change in lot size which prompted inventory costs to increase slightly as well. Once more the opposite effect occurred when production costs were decreased. Figure 12 and Figure 13 display the graphical results of the sensitivity analysis. The sensitivity analysis of MIP did not provide an insight into how the production and inventory costs could be affected. We suspect this is due to the limited number of trials we were able to run due to the lack of a professional solver license to speed up the computation. There were some differences observed but they were very minimal (non-significant) and performed with only 200 or less iterations – such a low number of iterations does not guarantee an optimal result. Again since we did not have the professional solver it is difficult to estimate the error in the results we did obtain.

Figure 12. Sensitivity analysis with regards to delta in inventory costs.
5.3 Summary

In this chapter we analyzed various lot size optimization methods as an alternative to the existing manual lot size determination method. We also looked at scheduling optimization algorithms which could facilitate scheduling of lot size jobs to machines at the manufacturing plants, a task which is currently also manual and very time intensive without the guarantee of an optimal solution. We studied three main lot size algorithms – EOQ, EOQ* and MIP, and two different scheduling algorithms – minimizing makespan and minimizing average weighted flow time. Both scheduling algorithms were NP hard and required heuristics, longest processing time (LPT) and shortest processing time (SPT), respectively. The combination of the lot size and scheduling algorithm determined that MIP-LPT is the best combination to use as it results in 100% ticket compliancy (for the products studied) and lowest cost. However, a big obstacle with using MIP is the need for a professional solver license which is able to perform several thousand iterations of the more than a thousand constraints all in less than minute. The open source license we used was very limited and resulted in the computations solving for more than 16 hours. This severely limited our sensitivity analysis work and scenario variation with MIP.
Chapter 6

Conclusion and Recommendations

6.1 Summary

This thesis work investigated a new decision-making framework for Company X which will enable the company to make better decisions about manufacturing their products under diverse manufacturing settings. We also examined production planning concepts of lot sizing and scheduling to improve the flow of the products in a specific manufacturing facility.

We studied an integrated production and supply chain system and hypothesized that there is no “one size fits all” solution when it comes to manufacturing products. Our analysis of two manufacturing systems demonstrated that it would behoove Company X to pursue a differentiated manufacturing strategy based on annual product volume. We showed this through a new, integrated performance metric which considers both manufacturing and supply chain costs. When inventory cost and manufacturing cost are both considered, results suggest that there should be two manufacturing strategies — one for large volume products and one for lower volume products. This result directly contradicts existing beliefs that inventory does not add to the product cost and all products should be produced under the same manufacturing setting.

We also investigated numerous lot sizing and scheduling algorithms and make a recommendation to use a mixed integer program and linear program to determine the optimal lot size and schedule, respectively. The MIP formulation examined included all of the parameters which were deemed important to the company — flexible time, inventory, holding and setup costs, and a capacity constraint. Although it did not result in a schedule sequence for the products, we
used an additional linear program sequence to schedule each product to an available machine and demonstrated most success with a longest processing time first heuristic.

6.2 Challenges ahead

In spite of the project success, we perceived some challenges ahead in its implementation. Namely, although the previous LGO projects, this one included, consider an integrated production and supply chain system, competing metrics between manufacturing and supply chain still prevail at Company X. In order to achieve some of the results demonstrated in this work, specifically the differentiated manufacturing strategy, the company will need to adopt an integrated systems level thinking – that is considering how success within one division will impact success in another division. We demonstrated that not accounting for inventory costs in the product cost can lead to higher than expected costs for some products, particularly those with lower demand that are still forced into the “largest lot size possible” mentality. Still, not all are aboard this train of thinking. More culture shifts must happen before the results of this work can be implemented company wide.

In our work we exhibited difficulties with the optimization algorithms predominantly due lack of professional solver licenses. We were unable to perform most of the sensitivity analyses due to an extraordinary amount of time it took to solve the model with the available open source optimization license. For the complexity of the variables the company would like to optimize, we believe that an optimization is the best way forward. However, in order to implement some of the algorithms we proposed, it is essential that the company invest in professional optimization software such as CPLEX or Gurobi\textsuperscript{7}. We also propose that the company invest time with simulation software such as ProModel or FlexSim. This will enable the company to test the lot sizing and scheduling algorithms through numerous simulations of different lot sizes and scheduling and observe beforehand the impacts on the manufacturing system. We utilized one such simulation software in our work and through the results we obtained readjusted some parameters within our models which improved the overall optimization.

\textsuperscript{7} An internal review of these has been done in collaboration of this project and has demonstrated success
6.3 Future work

There are numerous other projects which can be pursued by the company, the first being the implementation of the work described in this thesis. The analysis presented is based on theoretical models of an integrated production and supply chain system, as well as theoretical production planning models. We treated demand as deterministic and did not vary costs with time. Although the MIP model proposed can vary with time (and hence can vary the costs and demand), it is still based on certain demand. Future work can explore extensions of this model with regards to stochastic demand and variable costs. Finally a comparative analysis can be done between the theoretical results presented herein and any actual results obtained through implementation, including total delivered cost and optimization of product flow.

Our work with value stream mapping identified several opportunities for improvement in some of the manufacturing facilities at Company X. These improvements will fit well into the company's current operational improvement strategy. We identified WIP as a significant source of non-value added time. There is an opportunity to analyze product flow through facilities and understand the occurrence of WIP, and suggest methods in reducing WIP, which will effectively reduce the lead time for the product. There is also an opportunity to examine product flow and study how implementing dedicated lines for products or product families can reduce WIP and improve operational efficiencies within the plants. Finally, production planning was determined as another significant source of non-value added time. Implementing optimization techniques to determine lot sizing and product cycling is a substantial improvement which can be investigated.
7 Appendix

7.1 EOQ extension with Lagrange multiplier – derivation

\[ Q_i = \frac{\sqrt{2\lambda A_i D_i}}{h_i} \]  
\text{Equation 1}

- \( Q_i \) = lot size [units]
- \( A_i \) = setup cost per lot [$\text{lot}^{-1}$]
- \( D_i \) = demand per time [units/\text{year}]
- \( h_i \) = holding cost per unit per time [\$\text{unit}^{-1}\text{-year}]

\[ W = \sum \frac{a_i D_i}{Q_i} + \sum D_i R_i \]  
\text{Equation 2}

- \( W \) = available time [hours]
- \( a_i \) = setup time per lot [hours/\text{lot}^{-1}]
- \( D_i \) = demand per time [units/\text{year}]
- \( R_i \) = production rate [units/\text{hour}]
- \( Q_i \) = lot size [units]

\[ \lambda = \left( \frac{\sum D_i a_i}{W - \sum D_i R_i} \right)^2 \]  
\text{Equation 3}

- \( \lambda \) =
- \( A_i \) = setup cost per lot [$\text{lot}^{-1}$]
- \( a_i \) = setup time per lot [hours/\text{lot}^{-1}]
- \( h_i \) = holding cost per unit per time [\$\text{unit}^{-1}\text{-year}]
- \( R_i \) = production rate [\text{units/\text{hour}}]
- \( W \) = available time [hours]

\[ \lambda = \left( \frac{\sum a_i^2 D_i h_i}{W - \sum D_i R_i} \right)^2 \]  
\text{Equation 3}

- \( \lambda \) =
- \( A_i \) = setup cost per lot [$\text{lot}^{-1}$]
- \( a_i \) = setup time per lot [hours/\text{lot}^{-1}]
- \( h_i \) = holding cost per unit per time [\$\text{unit}^{-1}\text{-year}]
- \( R_i \) = production rate [\text{units/\text{hour}}]
- \( W \) = available time [hours]

\[ \lambda = \left( \frac{\sum a_i^2 D_i h_i}{W - \sum D_i R_i} \right)^2 \]  
\text{Equation 3}
8 References


