Improving Lead Time Setting and On-Time Delivery Commitments under Uncertain Supply Conditions

By

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Submitted to the MIT Sloan School of Management and the Department of Civil and Environmental Engineering in partial fulfillment of the requirements for the degrees of

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Abstract

As Dell seeks to continually improve customer experience, the company is identifying new and innovative ways to improve on-time delivery. Inventory shortages that occur prior to production account for approximately 35% of missed delivery dates. When these part shortages occur, demand planners must apply "extended" lead times to these parts to ensure that Dell's customers have the correct expectation for when their order will be delivered. This project focuses on part shortage problems and how to generate accurate lead times for customers commitments.

Previous research on the topic on lead time setting has focused predominately on buffering and measuring uncertainty in supply chains, which detail the benefits of having appropriate levels of safety stock and flexibility. However, prior research does not adequately describe methods for adjusting product lead times under uncertain supply conditions. The project develops a deterministic model for identifying when parts in Dell's supply chain require lead time adjustments due to supply shortages and then for setting the new lead times. Additionally, this project includes a statistical analysis of previous extended lead time events.

After a five-week testing period, the deterministic model was quite accurate in identifying what parts require extended lead times. This offers a 3% improvement in identifying when extended lead times are needed as it decreases human error in missed and late lead time extensions. Predominant sources of error resulted from backlog management issues, part deviations in production, and miscellaneous data errors. The statistical analysis yields two insights into part recovery in Dell's supply chain: (1) larger volume shortages take shorter time to recover than small volume shortages, and (2) approximately 80% of all part shortages recover within 10 days.

This research offers valuable insight into the problems associated with lead times in Dell's supply chain and recommends ways to best mitigate these errors. As Dell develops more robust and comprehensive databases on its inventory, future research can identify methods to accurately and automatically update lead times in real-time.

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Note on Proprietary Information

In order to protect proprietary Dell information, the data presented throughout this thesis has been altered and does not represent actual values used by Dell Inc. Any dollar values, product names or logistic network data has been disguised, altered, or converted to percentages in order to protect competitive information.

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Introduction

Dell is a major industry player in client, server, and storage products. As it seeks to gain new customers and improve its services to existing customers, Dell continually seeks ways to improve one of its core fundamentals: exceptional customer experience. After Michael Dell and Silver Lake Partners decided to take Dell from a public to private company in 2013, there has been renewed focus on improving customer satisfaction. One initiative launched following the re-privatization of the company was delivery promise, which is a tool designed to give customers the most accurate delivery date when purchasing through Dell. At its core, delivery promise relies on demand planners to enter accurate lead times for specific parts. In this project, customer lead time is defined as the amount of time from when an order is placed to when it will be delivered. This project focuses on finding how to set accurate lead times for Dell product parts under uncertain supply conditions. The goal of the project is to investigate tools and processes that demand planners at Dell can use to quickly identify part shortages and recommend the most accurate part lead time as possible.

1.1 Motivation

The motivation of this project came from analyzing how customer orders are processed through Dell's supply chain. All customer orders pass through three major processes in order fulfillment: payment, production, and logistics. Any delay in any of these processes can lead to delays in customer orders and, subsequently, orders being delivered late. Conversely, if each of these processes takes less time to complete than estimated, customers will receive orders too early. Historically, Dell's supply chain measured its performance against delivering orders on or before commitments to customers. This created a pressure to never deliver an order late and the customer lead time became overly conservative. Consequently, Dell had a very few late deliveries; however, over 30% of orders were arriving to customers earlier than the commitment. For some customers, receiving an order earlier than expected may not seem like an inconvenience; however, some customers may find receiving an order too early just as troublesome as receiving it too late. For example, if a large client reserved their IT department to receive a shipment on Thursday and it arrives on Tuesday, the client can be burdened to find the resources to deal with the early shipment.

To improve customer experience and decrease late and early orders, Dell has set ambition targets for its Global Operations team to improve order fulfillment performance by providing a more precise and predictive delivery experience to customers. This improvement initiative is largely focused on improving Dell's Perfect Order Index (POI), which is an industry standard for evaluating order fulfillment. Dell's Perfect Order Index measures performance by combining the four categories: on-time deliveries, complete orders, damage free orders, and correct paperwork. Since adopting the POI metric in 2015, Dell's Global Operations team has improved its on-time delivery performance by 12% on average, with on-time delivery defined as the percent of customer orders that were delivered completely on the date promised when ordered (i.e. orders not arriving early or late). Dell has set an internal goal of achieving industry standards in on-time delivery with gradual improvements from quarter to quarter. Dell's steady improvements in on-time performance are highlighted in Figure 1 below, which displays Dell's performance for on-time, late, and early orders over the past year for a sample region. Figure 1 does not account for orders that are delivered as incomplete to the customer, these orders are dealt with on a case-by-case basis by Dell's customer service.

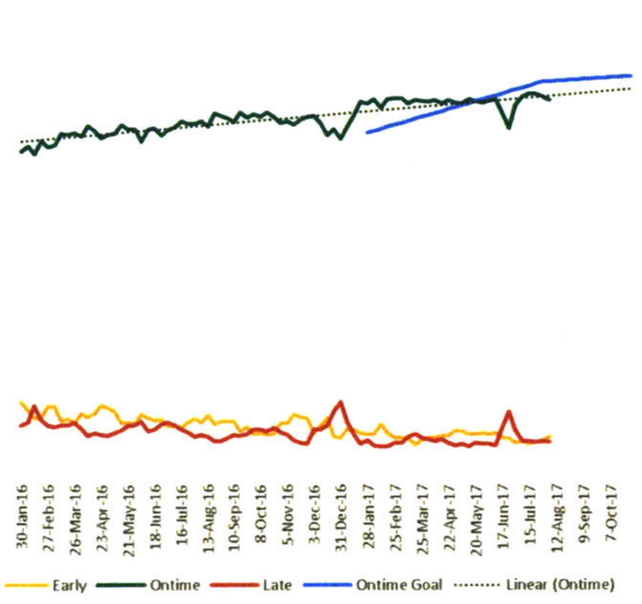

Figure 1. Dell's On-Time, Early, and Late Order Performance for a Sample Region over the past 12 Months

When orders are placed through Dell's ordering systems, product delivery times are estimated using an information technology tool. The specific process times for the individual processes are entered by Dell planners into the tool with input from operations, manufacturing, and logistics departments. With this information, the tool then adds the process times together for a total delivery time and date. For example, if payment processing takes 1 day, production takes 7 days, and logistics take 2 days, the total delivery time given to the customer will be 10 days. Through incremental improvements, Dell has improved the accuracy of delivery promises given to customers; however, variation in production process times account for a large volume of incorrect delivery dates promised to customers.

A key lever to ensure orders arrive on-time is the lead time applied to certain parts used for production. Each part in Dell's supply chain is given a standard lead time. Part manufacturing location, supplier, transportation method, final product, and other factors contribute to what lead time the part is given. This lead time is entered into delivery promise by a demand planner to help calculate the total production time and, subsequently, the total time to delivery of the order. These part lead times can be changed to account for variation in production or seasonal sales; often part lead times are extended to account for the shortages and other issues of the product part. There are myriad reasons why the part lead time may take longer than standard, such as customer changes, special orders, capacity issues, or quality issues. To identify what area to focus on for this project, a root cause analysis was conducted to identify what issue should be focused on for improving the lead time setting process. From this analysis, it was identified that part shortages prior to production account for approximately 35% of all late orders (or approximately 2% of all orders). Figure 2 below illustrates the breakdown of causes for late orders over a sample period of eight weeks.

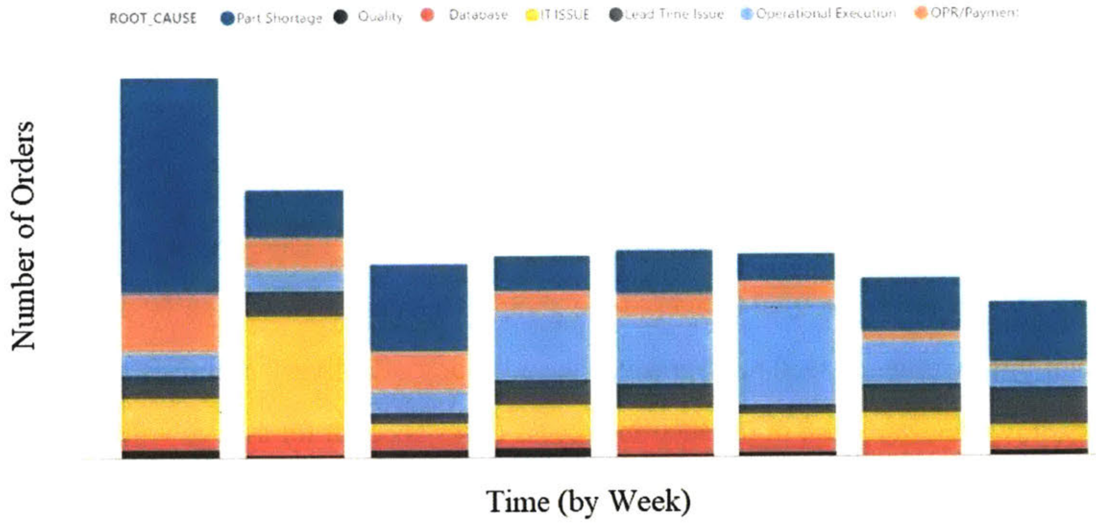

Figure 2. Late Orders by Cause for a Sample Period of Eight Weeks

When part shortages are known, demand planners can extend production lead times for certain parts to account for the time it takes to acquire the missing part. These extended lead times are entered into delivery promise to allow customers to get the most accurate delivery time when placing an order. When part shortages are missed, and lead times are not extended correctly, customer orders are negatively impacted. Likewise, even if a demand planner notices a part shortage, the planner may set the extended lead time for the part to an inaccurate time. Thus, Dell's order processing systems will provide the customer with an inaccurate delivery date. The motivation for this project lies in improving Dell's ability to accurately identify part shortages as soon as they occur and finding the most accurate adjusted part lead time. By quickly identifying part shortages and updating part lead times accurately, Dell can continue to improve on-time delivery performance and achieve greater customer satisfaction. For example, if Dell quotes a delivery to a corporate customer for a Thursday, that customer may reserve IT support or the loading dock area for Thursday. If that order then arrives on Tuesday or Friday, the customer must inconveniently shift resources due to the misquoted delivery time, hindering customer satisfaction.

1.2 Objectives

This project is focused on two main objectives to assist in Dell's on-time delivery performance. The first objective is on improving Dell's ability to identify part shortages in its supply chain. As Dell processes thousands of orders across the world at any given time, part shortages can cause significant disruptions to Dell's order fulfillment. Current processes for identifying part shortages are thorough but not always entirely effective. Developing a new methodology to quickly and efficiently alert a business unit when an extended lead time may be necessary can help Dell make incremental improvements to on-time delivery performance.

Another challenge Dell's demand planners face when adjusting lead times for a part shortage is finding the correct adjustment to apply. For example, if a demand planner does not know when a part shortage will recover, the planner may conservatively select ten days as the new extended lead time. Although this ten days may help avoid late orders, it may be too conservative of an adjustment and, consequently, orders can arrive too early. By offering Dell's demand planners an improved way to set the correct extended lead time for parts affected by shortages, customers can in turn receive more accurate delivery promises.

As Dell continues to reach for higher and higher on-time delivery performance, management and planners will need to constantly adapt and find ways to effectively implement new procedures. This project will include recommendations on ways Dell can decrease supply chain variability to improve delivery performance. Likewise, this project will offer recommendations on improvements to part-level data collection, which can lay the foundation for enhanced data-driven decision making and predictive lead time setting.

1.3 Hypothesis

This project hypothesizes part shortages can be predicted 90% accurately by using a deterministic analysis of inventory levels at separate time intervals. Using a deterministic model, extended lead times can be predicted by determining when part shortages recover. Likewise, if incoming supply is uncertain, a statistical analysis of previous recovery times can add intelligence to the planning process for setting lead times. This new framework will require comparing current inventory levels to levels required for fulfillment plus a safety factor. This analysis will need a high degree of accuracy for demand planners to base their selection of lead time. Furthermore, this deterministic analysis will need to be flexible enough to easily scale across more product lines and regions of Dell's supply chain.

This thesis also examines Dell's current processes and capabilities for how inventory shortages are detected and how lead times are adjusted. This examination will highlight potential opportunities for improvement, specifically how processes in data collection and management can increase the accuracy and precision of adjusted lead times.

1.4 Approach

To understand how Dell's order fulfillment process worked, this project involved collecting and analyzing both quantitative and qualitative data from multiple sources. The first step in this process involved mapping how customer orders are processed through Dell's complex supply chain, which functions differently based on if orders are built-to-order or built-to-stock. By mapping both information and material flows from customer order to final delivery, it is possible to better understand where barriers, decision points, data collection, and bottlenecks are located. With the process mapped, it was possible to identify specific areas to focus on and analyze how product lead times are affected.

The next phase of the project included gathering historic order level data to approve or reject initial assumptions about what are the major sources of variability causing delivery commitments to be missed. From this data set of historic orders, it was evident that variability in the material constraints and forecast volatility had the largest impact on late order deliveries. A further root cause analysis of late orders, as well as discussions with product line managers, validated that part shortages were consistently causing delays in manufacturing.

The following phase of the project involved selecting a variety of parts from Dell's supply chain to better understand what inventory levels were when extended lead times were added. Parts selected for analysis included parts that varied along different commodity types and transportation methods for replenishment. Part level data was aligned by using dates on which part lead times were extended to analyze what inventory levels, demand forecasts, and backlog levels could have predicted the lead time extension. From this, a deterministic framework was developed for how Dell can predict when a specific part will need an extended lead time.

The deterministic approach was then tested on over 300 parts across Dell's supply chain for a period of five weeks. The results of this testing period validated the deterministic approach for predicting extended lead times. Further data was gathered for the length of extended lead times for statistical analysis. This yielded valuable insight into the lengths of extended lead times when part replenishment is unknown. By combining both the deterministic framework for part level analysis and the statistical analysis of extended lead times, the project defines a reliable and efficient method for quickly identify when a part shortage occurred and what the length of the extended lead time should be.

Quantitative data for this project was collected through a variety of Dell's supply chain and ordering systems. It should be noted that the data at Dell is managed at different levels in order processing. For instance, data at the order and product level are typically very detailed with timestamps at each stage of fulfillment. The parts that combine to form the product and order are typically managed differently, often through suppliers or manufacturers. As lead times are set at the part level, gathering data at the part level became essential for the success of this project. Unfortunately, as parts in Dell's supply chain often only have a life cycle of 12 to 18 months, not all data sources on Dell's parts are robust or complete enough to leverage data mining techniques. Nevertheless, enough part level data is available to conduct an analysis of extended lead time events and identify predictors of part shortages. Qualitative data was gathered through a mix of individual discussions, attending meetings, shadowing demand planners in their daily work, or through conducting interviews. Combining all data sources regarding Dell's order processing and lead time setting process, this project was able to develop and test new methodologies and frameworks for improving Dell's on time delivery performance.

Literature Review

As this project is focused on improving Dell's on time delivery performance, a thorough review of research already conducted on the topics of lead time setting, supply chain uncertainty, and customer expectations was necessary.

2.1 Lead Time Setting

The term "lead time", defined as the length of time from process initiation to completion, has come to take on different meanings in the world of operations and manufacturing. Multiple academic papers have been published on the relationship between process lead time, order behavior, workload variability, and cycle times. The first area of research pertinent to this project involves understanding the *lead time syndrome*, which describes the relationship that as planners update lead time to adjust for missed orders they are unintentionally creating variability in their system that works against achieving on-time performance (Bendul and Knollmann).

Planned lead times, such as Dell's standard lead times for specific parts, are essential for any production and order process. To meet certain organizational goals (such as lower inventory, faster order fulfillment, high factory utilization), planners may frequently need to adjust planned lead times. While well-intentioned, the effect of the changing planned lead times creates uncontrolled release patterns. Figure 3 below best describes the *lead time syndrome*.

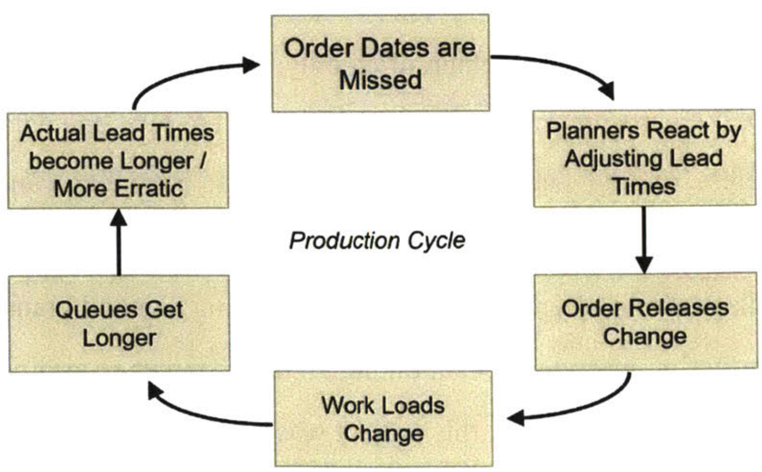

Figure 3. The cycle of the Lead Time Syndrome (Bendul and Knollmann)

The *lead time syndrome* is important to understand as Dell is seeking ways to implement dynamic lead times and new ways to update lead times based on changes in supply levels. Studied in detail, the *lead time syndrome* causes increases to average workload levels and flow times of orders, all of which can negatively impact customer orders (Selçuk et al.).

Another area of research regarding lead time setting pertinent to this project involves research of how lead time buffers should be accounted for in uncertain supply conditions. For certain production cycles of well-understood and stable-demanded products, often the greatest source of variability in production is the procurement process of specific parts. In their research paper, authors Hegedus and Hopp detail a lead time setting mechanism for determining precise lead times under stochastic supplier delivery times by using a combinatorial optimization method (Hegedus and Hopp). While a practical lead time setting tool, it requires precise knowledge and control of manufacturing conditions. As Dell relies on contract manufacturers and separate companies to manufacture and assemble many of its consumer products, this approach is not fully applicable for use in Dell's supply chain. Nevertheless, by studying this approach to lead time setting, when supplier parts are pulled into production cycles earlier, the supply chain obtains greater flexibility in meeting delivery commitments (Hegedus and Hopp).

2.2 Supply Chain Uncertainty

Considerable research has been conducted on the topic of mapping, measuring, and accounting for uncertainty in supply chains. As customers are demanding more and more competitive delivery times, supply chains across industries have had to adopt much higher levels of flexibility in their processes to meet these new demands (Angkiriwang et al.). Flexibility in supply chain environments may include multiple transportation methods, fluctuating production capacities, dealing with several suppliers, and so forth. One effective method by which companies build flexibility into their processes is through precise buffering rather than complex redesigning of systems (Angkiriwang et al.). A simple method of buffering would be to increase the safety stock of a product; likewise, buffering can mean having multiple methods of resupply or additional time for production cycles. Research of flexibility in supply chains expands beyond incorporating flexibility into internal processes but examine the benefits of having a flexible end-to-end supply chain.

While buffering may be an effective method to increase flexibility in supply chains, it is only one method of coping with uncertainty; considerable research has been conducted on strategies companies can use to reduce or eliminate certain types of supply chain uncertainties. Reduction strategies can include redesigning supply chain structures, supply chain control (i.e. where decision points are made), and supply chain information systems (Bhatnagar and Sohal). Another important strategy for decreasing uncertainties involve increasing collaboration across key suppliers and customers and through limiting the role of humans in the process (Bhatnagar and Sohal). Increasing collaboration across the supply chain has been described as a strategy to achieve the *seamless supply chain*, where all actors in the supply chain are closely integrated and, thereby, reduce uncertainties in demand and supply processes (Childerhouse and Towill). Similarly, by reducing the role of humans in the supply chain, greater efficiencies can be achieved through process automation and simplifying bureaucratic decision-making practices (Bhatnagar and Sohal). Although uncertainties will always exist in any supply chain or production process, Dell can make steady improvements to its on-time delivery performance by adopting and implementing strategies designed to both reduce and cope with supply chain uncertainties.

2.3 Tradeoffs in Meeting Customer Expectations

With the proliferation of the internet and e-commerce, it is no surprise that businesses have had to adapt to shifting customer expectations over the past decade. Dell has always been a fast adapter of technology, specifically with selling computers over the internet, where Dell registered its website years before its competitors (Dell and Fredman). Now, with ever-changing trends in globalization and international supply chains, customers are expecting faster delivery times and higher quality products. As companies struggle to meet shifting demands and fast deliveries, supply chains have grown more and more complex, such as companies relying on multiple suppliers of a single part or expanding warehouse locations to decrease transportation times. Complex supply chains often suffer from serious gaps between information and material flows, as well as making supply-chain monitoring an arduous task (Oláh et al.).

As Dell's supply chain continually changes to meet customer demands and business needs, it must balance investing in information technology systems and business processes. Described as the *business process dilemma*, business leaders often resist changing necessary business processes after making investment in new technology systems (Simchi-Levi). Leaders may make this flaw as they might have believed they only needed a technological solution to their problem. Unfortunately, failing to adjust human resources, information flow, job roles, and other processes for the new technology investment creates new sources of friction and inefficiencies. Author Simchi-Levi describes the *business process dilemma* by studying over 70 firms that made varying levels of investment in information technology and business processes. The study details that firms with high levels of investment in both fields, described as "mature", have lower inventory levels and associated carrying costs, decreased levels obsolescence of raw material, higher delivery performance, and higher levels of profitability (Simchi-Levi). Supply chain performance differences between immature firms (i.e. firms that do not invest in both technology and business processes) and best-in-class firms are displayed in Table 1 below.

Performance Measure	Business Type		
	Immature	Mature	Best-in-Class
Inventory Days of Supply (days)	101.2	78.8	66.3
Inventory Carrying Cost (% of revenue)	3.2%	2.3%	1.5%
Total Obsolescence Costs (% of revenue)	0.9%	0.5%	0.3%
On-time Delivery Performance (to requested date, %)	79%	88%	92%
Order Fulfillment Lead Time (days)	5.7	4.9	4.0

Table 1. Supply chain performance based on level of investment in IT systems and business processes (Simchi-Levi)

A firm understanding of the *business process dilemma* is essential as Dell strives to improve its on time delivery and supply chain performance. As Dell looks to investing in new technology systems, such as new supply chain monitoring tools or data mining and analysis systems, Dell must continually invest in its business processes to eliminate new inefficiencies and duplicated work from arising. This project seeks to add a new technology process for how part shortages are identified and acted on; and while this project may provide some benefits to the supply chain, Dell will see continued improvements by making strategic investment to improves its policies and procedures for lead time management.

Deterministic Inventory Model for Adjusting Lead Times

This chapter is focused on detailing the deterministic inventory model that was developed to identify what parts need extended lead times and find what the adjusted lead times should be set to. This model was designed to quickly and efficiently identify all parts of a given subset that require extended lead times and that might need an extended lead time soon. Likewise, this model can recommend what extended lead time should be set only if the next replenishment supply is known.

3.1 Model Components

This model was developed after conducting a thorough analysis of historic part-level data for specific commodities, specifically focused on when they were given an extended lead time. This data included inventory levels, incoming supply, demand forecasts, backlog levels, and actual customer demand. The goal of this model is not to prevent inventory shortages from occurring, but rather if we know inventory shortages will occur, how can a model accurately predict when a part needs an adjusted lead time and if the model can predict in the future when a part will need an extended lead time. As lead times at Dell are set and changed at the part level, analysis and testing were conducted using data on specific parts, such as processors, brackets, chassis, and keyboards.

The model is based on an equation comparing on-hand and inbound supply versus actual and forecasted demand, backlog levels, and a safety factor. On-hand supply refers to the inventory of the specific part Dell currently has at the manufacturing location or stored ready to use within 24 hours of the manufacturing site. Inbound supply refers to the inventory of a specific part Dell is tracking in its supply chain set to arrive within 24 hours to the manufacturing site. Forecasted demand is the amount of inventory Dell has predicted the manufacturing site will consume on a given day. Backlog level describes the amount of a specific part that is currently waiting to be used at the manufacturing site, this could also be accurately described as work-in-waiting. Actual demand refers to the actual volume of the part that is being consumed at the current time. As the actual demand is the correct volume of inventory used on a given day, this value helps in determining the forecast error, which forms the basis of the safety factor value.

The safety factor value is the product of a z-score value, the standard deviation of the forecast error, and the square root of the time interval for when the equation is being tested for. For example, when this equation is tested now, or when $t = 0$, the safety factor will result in a value of zero. This is because when $t = 0$ the actual values for sales are present, so it is possible to know exactly if the current supply covers the current demand and backlog. When the equation is tested into the future, or when $t = 1, 2, 3\ldots$, the safety factor plays a greater role in predicting if an inventory shortage will occur and if a lead time will need to be extended. For this project, a service level of 95% was assumed and the z-score was derived from taking the inverse of the standard normal distribution for this percentage value. The third and most important value in the safety factor is the standard deviation between the actual and forecasted demand for the specific part being tested. There are multiple ways to calculate and use the standard error deviation, such as over specific time intervals or averaging all available data. For this project, multiple approaches were taken for calculating and testing the standard deviation of forecast error with different impacts on the model results.

Combining all the values described, the equation listed in Table 2 below illustrates the deterministic approach to finding if a lead time will need to be changed (i.e. if a part shortage will occur) and what the new extended lead time should be (i.e. when the part recovers).

$\boldsymbol{S_{OH} + S_{IN} \geq B + D_f + z \cdot \theta \cdot \sqrt{t}}$	
where	S_{OH} = On-Hand Supply at time t
	S_{IN} = Inbound Supply at time t
	B = Backlog Level (work-in-waiting)
	D_f = Daily Forecasted Demand at time t
	z = Safety Factor, assuming 95% Service Level
	θ = Standard Deviation of Forecast Error
	t = time interval

Table 2. Deterministic equation for determining if an inventory shortage will occur with variable definitions

This equation is a powerful tool for determining when inventory shortages will occur, all depending on what time interval is used for testing. For this project, all time intervals used were day intervals (i.e. $t = 0$ is today, $t = 1$ is tomorrow, and so forth). Time intervals were tested at the daily level because Dell maintains and updates inventory data daily (although sometimes multiple times daily based on the database being used). If given correct and timely data, time intervals can be shifted to the hourly level for even greater prediction accuracy.

The following section will detail a numerical example for how the deterministic model works. First, the model will gather the necessary data for Chassis A. The model will gather the current on-hand supply, inbound supply, backlog level (or work-in-waiting), and the current demand for Chassis A. In this example, the current on-hand supply is 20 units, the inbound supply is 10 units, the backlog is 5 units, and the current demand forecast is 20 units. The model tests at the current period ($t = 0$) and, in this example, the supply is enough to cover the backlog and current demand ($20 + 10 > 5 + 20$). The deterministic equation is deemed to be True and, as a result, we do not recommend extending the lead time of Chassis A. On the other hand, if the current demand for Chassis A is 40 units, then the supply is insufficient to cover the backlog and current demand. Here, the deterministic equation does not hold, and the outcome is False (as $20 + 10 < 5 + 40$); as of time $t = 0$, there is shortage of 15 units.

We then apply the model to test the next period (i.e. $t = 1$, or tomorrow) in effort to find when the shortage of 15 will recover (when supply $\geq$ backlog + demand forecast). When the model moves to test the next period, it gathers the inbound supply and forecasted demand for tomorrow. In this example, suppose that the inbound supply is 50 units and the forecasted demand is 10 units at $t = 1$.

The deterministic model then tests the new values in the equation, where inbound supply must be greater than the shortage plus the new forecasted demand and the safety factor. At $t = 1$, the backlog B is now 15. The on-hand supply S_{ON} is now zero. The inbound supply S_{IN} is 50. Suppose that the inputted values for the safety factor and the standard deviation for the daily forecast is such that $z \cdot \theta \cdot \sqrt{t} = 5$, for t = 1. Then at $t = 1$, the model tests $50 > 15 + 10 + 5$. Here, the equation is True, signifying that Chassis A will recover tomorrow. The model then outputs for Chassis A for the lead time to be extended by 1 day.

If the equation were False for Chassis A at $t = 1$, it will move to $t = 2$ and repeat the same process. That is, we will project how much on-hand inventory (S_{IN}) or shortfall (B) that we expect to have at the start of period $t = 2$. We will then use the forecast of inbound supply and the forecast daily demand for $t = 2$, along with the safety buffer, given by $\cdot\, \theta \cdot \sqrt{t}$, to apply the test given by the above model. If the result of the test were true, then we extend the lead time to 2 periods, and we are done. If the result of the test were false, then we increase t by one, and repeat the process. If we reach $t = 14$, and have not obtained a True outcome, then the model will output that the lead time must be extended greater than 14 days for Chassis A.

3.2 Lead Time Prediction

In addition to determining if a part requires an extended lead time now or in the near future, the deterministic method detailed in the previous section also can find the correct extended lead time that should be set. The model begins by testing at $t = 0$, on the present day, using supply and demand values pulled from Dell's database. When the model tests a certain part, Part X for example, if the equation is True today, then no extended lead time is required, and Part X will remain on its standard lead time for production and delivery. However, when the equation result is False for Part X today, the equation will flag Part X and move onto the next step and determine what the new lead time should be. The deterministic model will move forward one interval, or day (i.e. to tomorrow), and test if the equation is True or False at that time. For instance, if Part X tests False today, at $t = 0$, then it will automatically test tomorrow, $t = 1$, to test if the on-hand and inbound supply will be greater than the summation of backlog and all forecasted demand for the shortage period. When the model moves to the next period to test, it tests if the on-hand and inbound supply for that period will satisfy the shortage amount plus the forecasted demand for that time. On-hand supply does not change as the model already detects there is insufficient supply to cover demand; the model is looking forward if enough inbound supply arrives at that time to satisfy the growing shortage amount. If the equation tests True, then the model will recommend setting the extended lead time for Part X to 1 day. Thus, the demand planners at Dell can adjust the part lead time by one day to account for the shortage and, thereby, improve the timely update and accuracy of part lead times.

It is important to note that the equation begins testing time intervals into the future beyond the next period, or when $t = 1$, that the forecasted demand is the summation of all forecasted demand that occurred during the shortage. For example, if Part X is short by a volume of 20 at $t = 0$, and at $t = 1$ the demand forecasted is 10 but there is still insufficient supply to meet the total shortage of 30, the model will move to the next period and test again. If at $t = 2$ another 10 Part Xs are forecasted and the equation is still False, the total shortage is now 40 (plus the safety factor value) to be tested in the next period. It is important to note that this model does not account for partial recovery of part shortages. Partial recoveries occur when a limited amount of supply comes in for a specific part but not enough to cover the full shortage. For instance, if inbound supply at $t = 2$ was only 20, it would have not covered the full shortage of 40, and order would still go unfulfilled. As partial shortages are dealt with on a case-by-case basis in Dell's supply chain, the exception cases of partial shortages are not accounted for in the model and it continues to test for when the part fully recovers and suggests that as the new extended lead time.

Figure 4 below displays a simplified sample output of the model identifying specific parts that are experiencing shortages as well as including recommendations for what the adjusted lead time should be (i.e. when the model moved forward in time periods and identified when the part shortage recovers).

Part	Recommended EXT	Reason	Future Prediction?
Example Part - Cover A	Extend to: 8	Supply Shortage of 209	Short in next 24
Example Part - Base A	Extend to: 7	Supply Shortage of 12	Short in next 24
Example Part - Bezel A	Extend to: 7	Supply Shortage of 242	Short in next 24
Example Part - Palmrest A	Extend to: 4	Supply Shortage of 8	Short in next 24
Example Part - LCD Screen A	Extend to: 3	Supply Shortage of 271	Short in next 24
Example Part - Bezel B	Extend to: 1	Supply Shortage of 7	Short in next 24
Example Part - Chassis A	Extend to: >14	Supply Shortage of 90	Short in next 24
Example Part - LCD Screen B	Extend to: >14	Supply Shortage of 68	Short in next 24
Example Part - Chassis B	Extend to: >14	Supply Shortage of 6627	Short in next 24
Example Part - Chassis C	Extend to: >14	Supply Shortage of 649	Short in next 24
Example Part - Palmrest B	Extend to: >14	Supply Shortage of 64	Short in next 24
Example Part - Palmrest C	--	--	Short in next 24
Example Part - Chassis D	--	--	Short in next 24
Example Part - Base B	--	--	--
Example Part - Chassis E	--	--	--
Example Part - Chassis F	--	--	--

Figure 4. Sample output of the deterministic model identifying specific parts currently short and what the extended lead time should be set to

Figure 4 illustrates another capability of the deterministic model, which is its ability to predict if part shortages will occur in the following time periods. "Short in next 24" explains that the part listed tests False at $t = 1$ and it will again be short in the next 24 hours. Nearly all parts listed in the sample output test as short in the next 24 hours but two of the parts listed are not currently short but will go short in the next 24 hours. This displays the predictive capabilities of the deterministic approach, which can alert demand planners if a shortage is likely to occur in the following days or weeks (i.e. at $t = 1, 2, 3...$).

These predictions from the models are not absolutes if the part will go short on the predicted time or not, they are best estimations given the data sources available and assumptions made in the model. The only period when the model result is accurate is at the current time, or when $t = 0$, as the actual demand values are known, and the part is moving through the production cycles. As the model tests at time intervals into the future, uncertainty of future demand and forecast errors contribute to uncertainty in the model results. As the period being tested becomes further and further from the present, the model results become less and less accurate over time. Along with the fact that Dell only forecasts at the daily level roughly three to four weeks into the future, the model limits its analysis to only two weeks into the future. When the model displays an output of "Extend to: >14", this means that the model does not see an incoming supply in the next two weeks and, thus, cannot predict what the correct extended lead time should be. In this case, the demand planner will need to determine what is the best extended lead time given limited information. This situation will be examined further in the following chapter of this thesis.

The safety factor also plays a significant role in determining if future on hand and inbound supply will be sufficient to cover the business needs. As discussed before, the safety factor in the deterministic equation is the product of the z-factor, the standard deviation of forecast error, and the square root of the time interval. Based on its design, the value of the safety factor increases with each period, which is illustrated in Figure 5 below.

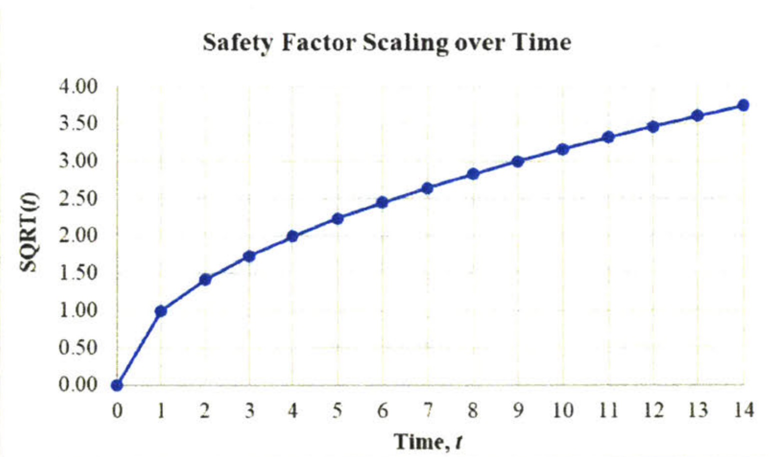

Figure 5. Multiplying factor by with the safety factor increases in each period (in days)

Assuming at 95% service level for the z-score, this value was calculated as approximately 1.644 in all testing of the safety factor. If the service level is decreased, to 90% or 85% for example, the z-score value would decrease, thereby decreasing the total value of the safety factor. The final factor comprising the safety factor is the standard deviation of forecast error. As the z-score and square root of the time factor are both multipliers, the standard deviation of forecast error has the greatest variability with each part being tested. If the forecast error was particularly high for a certain part, the safety factor value was significantly higher than if forecast error had been lower. Forecast error was calculated using the mean of absolute error (or deviation) between part sales and part forecasts over the past fourteen days (i.e. when $t = -14, -13, -12...$). The mean absolute error was used over the root mean square error because it does not overly skew the safety factor element of the model as the absolute mean error does not penalize large errors as much as the root mean square error equation. As no forecasting method is perfect, there are often variances between the predicted and actual demand for a certain product or part. When the root mean square error was used to calculate the standard deviation in the safety factor, the size of the safety factor increased significantly. Adding a significantly high safety factor for a certain part in Dell's supply chain would be an unrealistic solution as it would increase inventory costs unreasonably. Thus, the mean absolute deviation was used to calculate the forecast error. The mean of absolute error over the past four weeks was total amount of data available to analyze. It is important to note that all testing was done with the best available data; some data sources are not complete for certain products or missing altogether. Best estimations were used to find the standard deviation values for parts being tested.

When all values are combined, the deterministic equation tests if on-hand and inbound supply will be greater than or equal to the summation of backlog, forecasted demand, and a safety factor. Figure 6 below is a depiction of how each value compares to each other for a sample part.

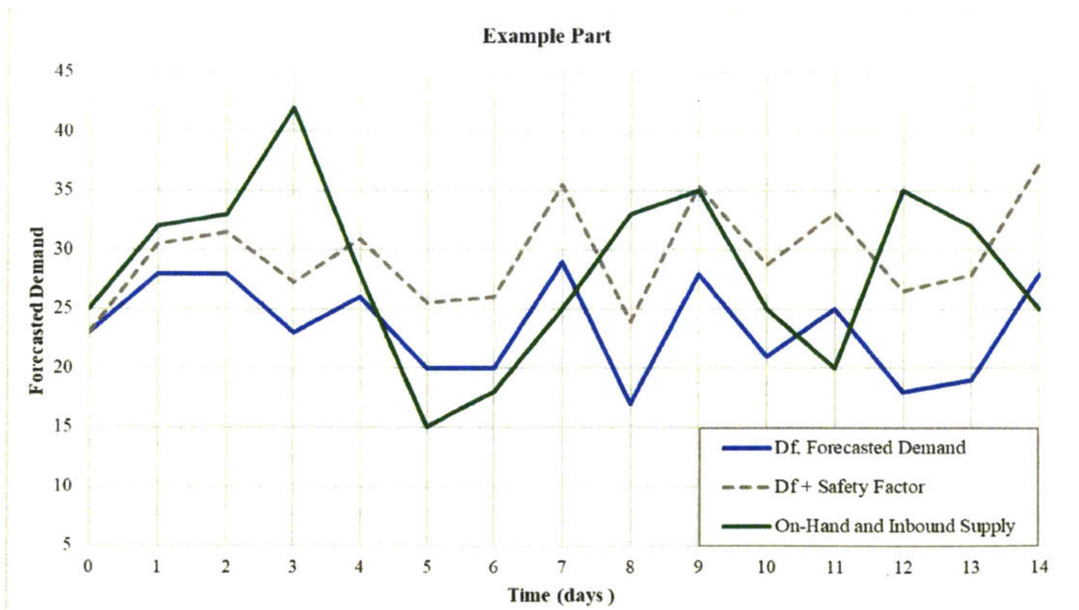

Figure 6. Display of deterministic equation testing methodology for a sample part

In Figure 6, it is possible to see the projected supply and forecasted demand levels in comparison to one another. The dashed line represents the forecasted demand plus the safety factor for the adjusted required inventory amount. As the safety factor grows with each period, the size of inventory required grows. This has implications on how the deterministic equation predicts when a part will go short and required a lead time adjustment. Using the example part in Figure 6, it is evident that, without accounting for the safety factor, there would be time differences in when parts went short. For instance, with no safety factor, the example part was predicted to go short on $t = 5$, when it could more likely go short at $t = 4$. Likewise, without considering the safety factor, planners may have predicted the part will recover at $t = 7$, when it may in fact recover at $t = 8$. These small changes to lead time prediction can impact how demand planner adjust lead times for part and, thereby, affect the delivery promises given to customers. Although there are no certainties in the predictions from the deterministic approach, the results are best estimations for identifying parts that are currently short or will likely go short in the next 14 days and suggesting what the adjusted (or extended) lead time should set to.

3.3 Performance and Evaluation

Once the deterministic approach was developed and approved, a testing period was conducted to evaluate the model's performance and validate its applicability to Dell's processes. The testing period was designed to compare the results of the model to the processes of Dell's demand planners, which is the method by which Dell identifies part shortages and adjusts lead times. The model tested 324 parts over a five-week period with the results of the model (i.e. identified and predicted part shortages) compared to actual part shortages. The parts being tested were individual ordered consumer products, such as individual laptop and desktop computers customers and businesses would order from Dell. Direct sales of client products were selected as they offered a steady demand, forecasted demand, supply, and sales data; rather than, for example, retail related products which have predictable but abnormally high demand spikes that are dealt with on a case-by-case basis. Of the 324 parts tested, part types included motherboards, chassis, covers, LCD screens, palm rests, graphics cards, processors, bezels, solid-state memory drives, hard drives, RAM memory card, and other parts for laptop and desktop computers. The variety of parts selected was intended to include high and low value parts as well as parts that are resupplied through different transportation methods, such as high values by air and low value items by sea. For instance, processors are typically higher value items and shipped via air while chassis are lower value, larger items shipped by sea.

The model was tested with parts managed by three different demand planners in Dell's consumer product planning organization, which was to diminish the bias individual demand planners could have on identifying part shortages and adjusting lead times. For example, one demand planner may be very proactive in managing his or her parts and frequently check for part shortages, while another demand planner could be more reactive in managing his or her assigned parts. These three demand planners were assumed to be representative of the planning organization for adjusting lead times. The model tested all parts on every work day of the week. When the model tested each part, it ran the data for each part through the deterministic equation detailed in Table 2. After all selected parts were tested, the output identified each part that required an extended lead time. If the inbound supply in the next two weeks was present, an extended lead time would be recommended. Likewise, if the part was not currently short but the model identified that it would go short in the next two weeks, the model would output the days until the expected shortage. An example output of the model can be seen in Figure 4. At the end of every week, the model results were compared to the demand planner processes as well as the actual shortages that occurred in Dell's supply chain. By consulting with each demand planner at the end of every week, specific errors or exceptions could be identified and accounted for. This data gathering method helped to identify what was causing error in the model and how it could best be addressed. One area where demand planner feedback was used to improve the model during testing was on the number of parts being tested. For example, the testing period started with a total of 403 parts being tested; however, many of those initial parts either had recently reached their end-of-life in Dell's supply chain or had other case-by-case problems in testing. This feedback helped adjust the number of parts being tested until a final number of 324 parts were tested. Each part was observed each day during a 25-day testing period; in addition to the initial 403 parts tested and the final 324 parts tests, a total of 8,205 observations were recorded. Each observation resulted with the model deciding whether to extend the lead time of the part tested or not to extend the lead time. These observations were compared to the actual inventory levels to test the accuracy of the model which included delayed customer orders. Observations were also compared to the results of the demand planners to gain better understanding if and how demand planners predicted the shortage and where improvement opportunities lie. After the five-week testing period, all results were compiled and analyzed to find if the deterministic method improved on current processes and, if so, by how much.

After compiling all results, a confusion matrix was used to analyze the model's performance. A confusion matrix, or error matrix, is a statistical classification layout that allows visual representation of an algorithm or model results. Each row in the confusion matrix represents the predicted instances while each column represents the actual instances during a testing period. From the confusion matrix of this analysis, the model's accuracy, misclassification, true-positive, and false-positive rates can be derived. Figures 7 and 8 below displays the confusion matrix and model performance of all parts tested over the five-week period.

Model Predict	Actual Shortages	
	Extend	No
Extend	441	1209
No	12	6543

Figure 7. Confusion matrix of deterministic model results for five-week testing period

Overall Performance (5 Weeks)	
Accuracy	85%
Misclassification	15%
True-Positive	98%
False-Postive	16%

Figure 8. Model performance when compared to actual shortages over testing period

Each number in the confusion matrix in Figure 7 represents a single model prediction. For example, of the parts being tested there were a total of 453 real part shortages that occurred, and the model correctly captured 441 of those events. Using the results in the confusion matrix, the model performance, shown in Figure 8, was determined. The false-positive rate is the percent of all negatives that test positive: in this example it is the percent of all no-shortage instances for which the model predicts a shortage, namely 16% = 1209/ (1209+6543). This number was higher than expected as it undermines the overall accuracy of the model. When the false-positive rate was examined in greater detail, there were three main sources of error that contributed to the high false-positive rate: (1) discrepancies between backlog volume and forecasted inventory in Dell's supply chain, (2) part level deviations that cause short parts to be replaced with other available parts, and (3) other errors (such as unaccounted inventory) in Dell's supply chain. Each of these error sources will be explained in greater detail in the recommendations section of this thesis.

The true-positive rate for the model performance details when there is an actual shortage, what percentage of these are predicted accurately by the model (98% = 441/ (441 + 12)). Over the entire five-week testing period, there were only 12 instances in which the model failed to predict an extension for a part when it truly needed an extended lead time. A 98% true-positive rate is a strong performance indicator for the model's performance as when the model outputs a list of parts that all need extended lead times, there is only a 2% likelihood that a part that needs extension is not on that list. Combining all false predictions or missed predictions, the total misclassification rate for the model is 15% and overall accuracy of the model at 85%.

3.4 Sources of Error

Several factors contribute to the 15% misclassification rate of the deterministic model and by understanding the sources of error, improvements can be made to the model to improve on time delivery performance. The three main sources of error contributing to the accuracy rate of the model being approximately 5% less than initially hypothesized were (1) backlog volumes interfering with forecasted inventory in Dell's supply chain, (2) part level deviations that cause short parts to be replaced with other available parts, and (3) other errors in Dell's supply chain and information technology systems. Figure 9 below depicts the approximately amounts each error source in the model results.

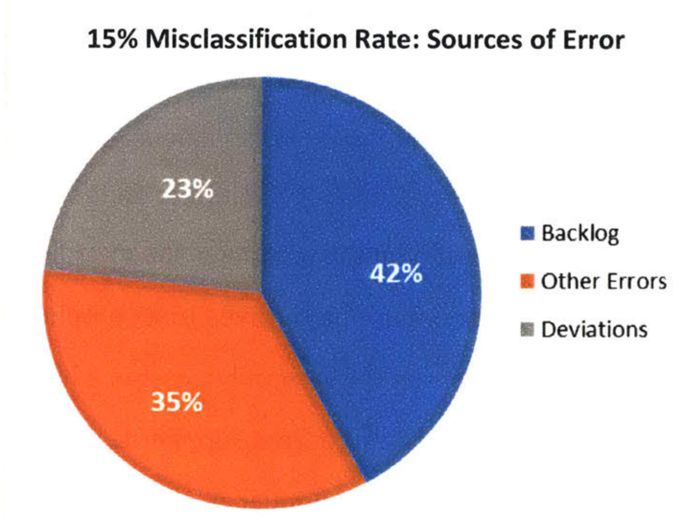

Figure 9. Error sources of the deterministic method results from five-week testing period

The largest source of error that negatively impacted the model performance was backlog value interfering with future lead time predictions. Currently, Dell structures its backlog by combining all future planned orders and all current orders in its backlog into one value displayed at $t = 0$. The means that if Dell has a planned order in ten days from now, at $t = 10$, it will not begin constructing the order at $t = 0$ as there still is 10 days for inventory to arrive to prepare for production. Unfortunately, the volume of that order is simply added to the current backlog volume. Therefore, when the model is applied to the data, the deterministic model sees a very large backlog volume at $t = 0$ and, according to the rules of the model, outputs that the current on-hand and inbound inventory volumes will not cover what is required. However, when a demand planner looks at the data using their understanding of orders being processed through Dell's systems, they understand there is currently enough inventory to complete planned orders for $t = 0$ and that the high backlog value is due to a future planned order at $t = 10$; and therefore, they do not need to adjust lead times as there is no current inventory shortage. Dell has plans to restructure how its backlog is accounted for in its information technology systems so that future planned orders are not lumped in with the backlog value at $t = 0$; when that change occurs, the model will no longer see all orders at $t = 0$ and be able to compare future backlog values to future inventory volumes, increasing the accuracy of the model outputs. With this fix, the model could decrease its misclassification rate by as much as 6%, thereby improving the model accuracy to over 90%.

A second source of error that decreased the accuracy of the deterministic model results was part deviations in Dell's supply chain. Part substitutions, or deviations, occur when one part of a product can be swapped for another part with no negative effect on the quality or manufacturing speed of the final product. For example, if a laptop computer for an order was assigned a hard drive from supplier A, but suppose that no more hard drives from supplier A are available. In this case, a planner will notice the problem in the system but assign a hard drive from supplier B to fulfill the requirement. So long as the hard drive from supplier B meets all the technical and performance specification of the hard drive from supplier A, there will be no defect in the quality of the laptop. By deviating to similar available parts when inventory runs short, Dell can fulfill orders quickly with no interruptions to the production cycle. Unfortunately, all part deviations are decided and acted on manually by planners or manufacturers; and therefore, the model cannot automatically capture what part shortages can be fulfilled by a similar part on hand and what shortages required a replenishment order. When the deterministic model sees that a certain part required is not available for production, it will output that specific part as short and recommend an extended lead time adjustment. Demand planners seeing that output understand that the part is short, but it can be replaced by a similar part and therefore no lead time adjustment is necessary. Having substitutable parts provides Dell with a flexibility to allow uninterrupted production flows but makes it difficult, with the current information technology systems, to adequately capture what shortages require new lead times.

The final and most difficult source of error in the model results was that of miscellaneous errors in Dell's supply chain systems. When the model output a false-flag value, if it was not a backlog or part deviation problem, the error typically was caused due to various, case-by-case reasons. Some of the errors were caused by unaccounted for inventory in Dell's supply chain, part level quality issues, errors in information technology systems, unplanned large orders, or unexpected fluctuations in demand due to seasonality. Many of these errors were dealt with on a case-by-case basis with no real identifiable pattern in frequency. As no supply chain operates perfectly, these miscellaneous errors cannot be entirely avoided; but as these errors are slowly identified and remediated, the accuracy of the model can be steadily improved.

3.5 Impact on Business Performance

While the accuracy of the model ended up being about 5% less accurate than initially predicted, the 85% accuracy is about a 3% improvement over current processes used for identifying inventory shortages and what lead times should be adjusted to. Although it is difficult to accurately measure how well individual demand planners identify and act on inventory shortages, current processes and procedures capture roughly 80 to 82% of all part shortages. When analyzing current processes, the greatest source of misclassification often involves not predicting a part shortage (i.e. extending the lead time) when a shortage has occurred; this accounted for roughly 14% to 18% of the misclassification events. Oppositely, it is rare that when there is no part shortage, demand planners falsely predict the part is short. Causes for this accuracy include discrepancies between individual demand planners, variability in demand and sales, unexpected large orders, limitations of current data sources, individual part exceptions, procedural or human error, and so forth. While the deterministic framework does have certain drawbacks (i.e. high false-positive rate), it helps to simplify and baseline the procedures for identifying and acting on inventory shortages. At this stage, the model outputs cannot be automatically updated in Dell's lead time systems and they must still be verified and acted on by individual demand planners. The benefit to demand planners is through eliminating many individual parts that do not need to be acted on each day. For example, each demand planner is responsible for managing somewhere between 100 to 300 individual parts depending on their area of responsibility. As inventory levels change daily (sometimes hourly), it is difficult for demand planners to keep up with inventory levels and, as a result, they can miss part shortages and fail to extend lead times accordingly. By using the deterministic model to quickly test and analyze all parts, the model can output only the parts that are flagged and need to be acted on.

The benefit to the demand planner being that instead of having to look at 300 parts, they only need to pay attention to 30 or so parts the deterministic model flagged for needed extended lead times.

In addition to narrowing the field of parts demand planners need to check and analyze on any given day, the deterministic model is an approximately 3% improvement in identifying when extended lead times are required when compared to how lead times are detected as it able to improve on missing to identify part shortages and late reactions to inventory shortages. This became evident when the results of the model were compared to the demand planner's action for the tested parts, certain parts the demand planners missed or were late to react to. For example, a demand planner extended the lead time for a specific part on Friday because he realized inventory was insufficient to meet demand. However, the model identified that the part was short on Wednesday; and in this case, the lead time for the part should have been updated on Wednesday, which would impact the delivery dates customers receive when placing an order from Dell. Likewise, when the model results were compared to the demand planner's management of his or her parts, some inventory shortages were missed altogether by the demand planner but not by the deterministic model. These two areas are where the deterministic model offers the 3% benefit over current processes: by assisting in decreasing the amount of missed inventory shortages and late reactions to inventory shortages.

Statistical Analysis of Extended Lead Time Events

The second main area of examination for this thesis is a statistical analysis of historical extended lead time events in Dell's supply chain. This analysis involved gathering and analyzing data involving when parts were placed on extended lead times, specifically trying to determine ways that the accuracy of future extended leaded could be improved. The goal of this analysis is to add intelligence to the process of adjusting lead times in Dell's supply chain and, thereby, improving Dell's on time delivery performance.

4.1 Measuring Extended Lead Times

Dell's supply chain performance is heavily monitored at the order level, such as measuring how many orders enter production, how many orders ship, how many orders arrive on time, and so forth. As lead times in Dell's supply chain are largely managed at the part level and given how Dell's data systems are structured, it is challenging to draw connections between specific orders that arrive late and what specific part or lead time caused the delay. Likewise, based on the data available in Dell's delivery promise system, there is no method to determine what an extended lead time actually needed to be (i.e. when the part actually recovered). For example, if a demand planner realized that Part X was short on inventory and needed an extended lead time, the demand planner may have extended Part X's lead time to 10 days, but it recovered in 5 days. When this happens, the demand planner typically needs to reenter the system and remove the remaining extended lead time at day 5. Unfortunately, in this example, any customers that placed orders involving Part X during that time received an incorrect delivery date; that is, they were told 10 days to delivery but received the package 5 days prior to delivery. In this example, the demand planner was overly conservative in setting the extended lead time, which may have prevented a late order from occurring but caused an order to arrive too early to a customer and, thereby, negatively impacting Dell's on time delivery performance.

While discrepancies between predicted and actual part recovery times may seem negligible in the overall picture of Dell's supply chain, they negatively impact supply chain performance. This project was one of the first examinations of how parts in Dell's supply chain recover from inventory shortages and what the implications are for future extended lead time events. For a three-month period, times of inventory shortages were recorded along with part type and volumes of shortages. Data gathering was conducted through an automatic process in Dell's inventory management systems. Parts gathered for analysis included parts for laptop and desktop computers, such as motherboards, bezels, chassis, covers, graphics cards, processors, hard drives, and so forth.

The inventory system counted every day that a specific part was short and counted the days until it recovered. A specific part is considered short when it is required (i.e. forecasted or needed for customer orders) and is not on-hand or expected to arrive by the time it is needed. A part is considered recovered when the part arrives for assembly and the amount received satisfies all demand that was incurred during the shortage period (i.e. no partial recoveries). This way the system recorded exactly when the inventory shortage occurred and exactly when the inventory recovered. These values were exactly the length of time it took the parts to recover after going short and hence these are the values that the extended lead times should have been set to. Again, given how Dell's inventory and lead time management are structured, it was outside the scope of this project due to project timelines to determine what the predicted lead times for these specific parts were given the time limitations of this project. Nevertheless, the data gathered provides valuable insights into how parts in Dell's supply chain recover from shortages, which in turn provides an added layer of intelligence for how lead times are set and adjusted.

4.2 Impact of Volume on Recovery Time

The first and most notable feature of the recovery time analysis was the relationship that volume of shortages played on the recover times. Having an inverse relationship, it seemed that the larger the inventory shortage was the shorter time it took to recover from the shortage. In this analysis, inventory shortages are defined as any instance in which on-hand and inbound supply of a part was less than the forecasted demand for a specific part. Likewise, when the volume of inventory shortage was smaller, it took longer for that individual part to recover. When this is thought of intuitively, it makes sense that larger volumes take shorter time to recover from shortages as managers, planners, and process owners are likely aware a large volume is short and is affecting multiple orders. This awareness and attention likely result in suppliers being contacted and part volumes brought in faster or other parts being used to fulfill the shortages. Figure 10 below details the results of a scatterplot analysis between shortage volume and days to recover for over 2000 inventory shortage events. In this analysis, the size of inventory shortages is defined as the peak amount of forecasted demand that the on-hand and inbound supply failed to satisfy in a given period. Not accounting for partial recoveries, the peak amount of forecasted demand for a certain shortage occurs the period prior to its full recovery.

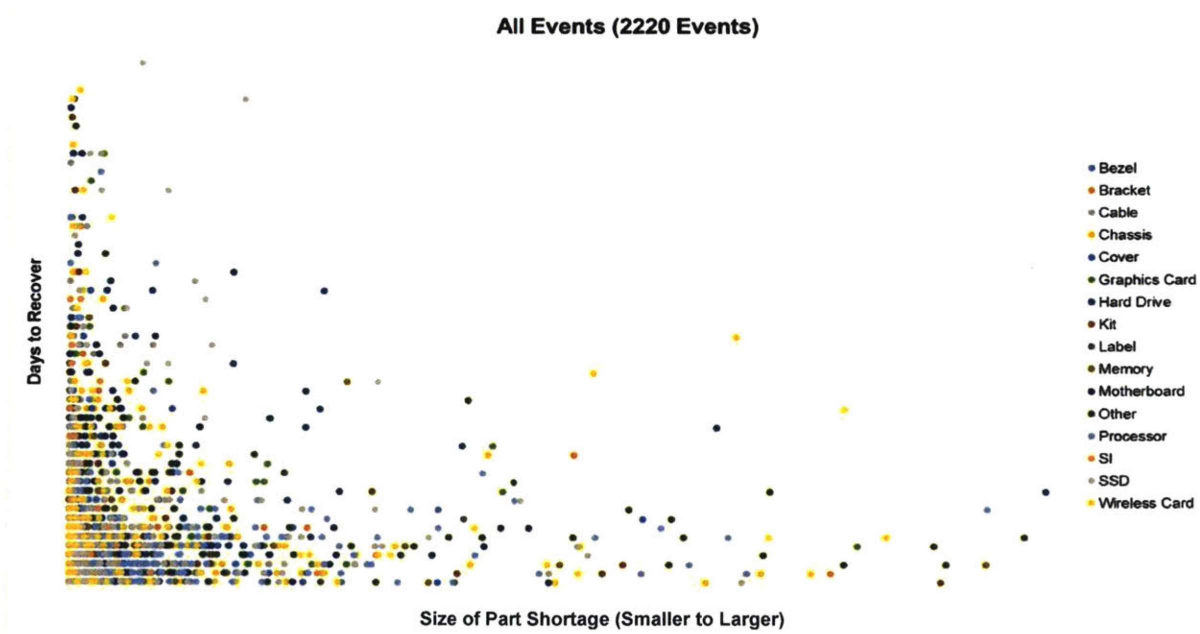

Figure 10. Scatter plot of part shortage volume and length of recovery time

Figure 10 above illustrates the inverse relationship between the size of inventory shortage and how long it takes for the part to recover. Moreover, this inverse relationship seems to be true across high and low value commodities. This insight is valuable for how policies and procedures are set for adjusting lead times based on inventory shortages. For instance, if a demand planner knows he or she must adjust the lead time for a specific part suffering a large shortage and the specific recovery time is not known, he or she may intuitively want to adjust the lead time for a larger time (i.e. larger the shortage, larger the recovery time). However, if the demand planner understands the inverse relationship between shortage volume and recovery time, he or she will set the extended lead time to a shorter time. Additionally, if the data sources are well managed and easily accessible, a demand planner could look up a specific part number or commodity type to quickly reference historic data for how many times that part when short, how large the shortage volumes were, and how long it took to recover from the shortage. Although it is important to realize that historic recovery times do not necessarily predict future performance, the process of adjusting lead times can be improved by using historic data to draw insights about the relationships between shortage volume and recovery time.

4.3 Distribution of Extended Lead Times

Another area of analysis of how parts recover from shortages in Dell's supply chain is the distribution of days to recover. This analysis used the same data source as the analysis into the relationship between shortage volume and time to recover. Using the exact times that parts took to recover from shortages in Dell's supply chain over a three-month period, a distribution was created to understand the frequency of specific recovery times, which is shown in Figure 11 below.

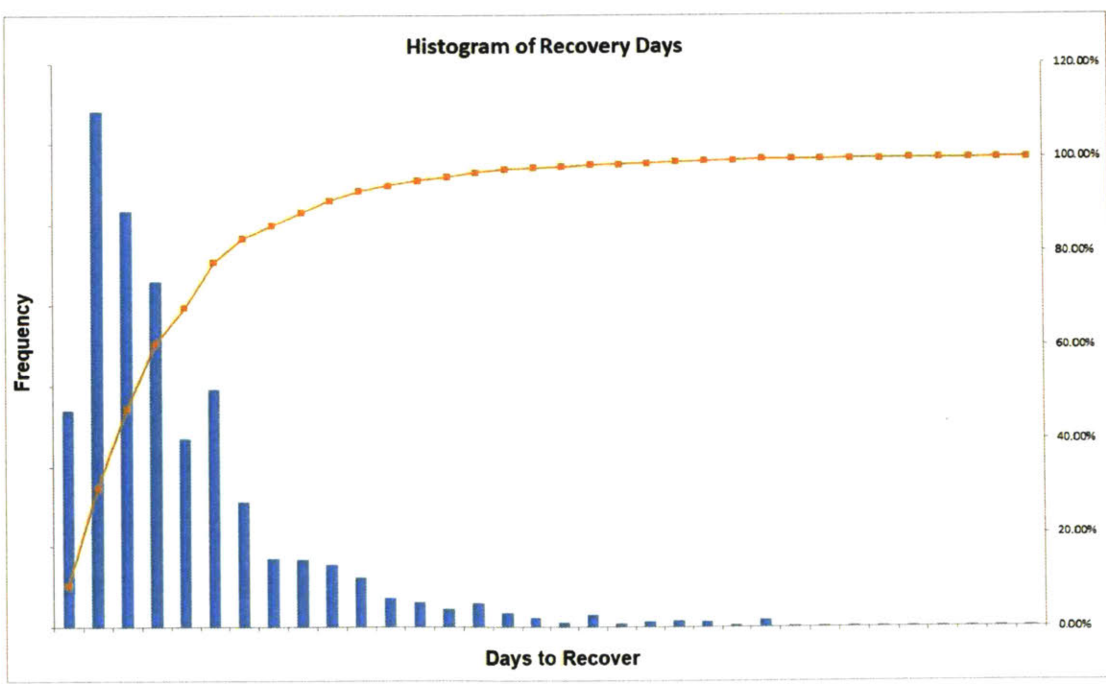

Figure 11. Frequency distribution for recovery times of shortages over a three-month period

Using a frequency distribution for recovery times, it is evident that a large majority of part shortages in Dell's supply chain recover in a relatively short time period. Specifically, roughly 80% of all parts recovered within 12 days from when the shortage occurred, with a large majority of recoveries happening between 1-3 days after the shortage occurred. While the analysis does show that there is a long tail of a few shortage events that took longer than 12 days to recover, most of all part shortages either recover quickly or within a 10-day period. Many of the recoveries that took greater than 12 days often had individual exceptions, such as very low-running products, customer-initiated changes, batch quality issues, or orders that utilized parts that had reached their end of life. Many of these cases are dealt with individually by sales or operations managers, which make them difficult to evenly account for. This insight is valuable to demand planners as it shows that, if it is unknown when the next replenishment of supply will arrive, there is a good likelihood that it will arrive before or at 10 days. As demand planners can sometimes be overly conservative when a part shortage occurs, this insight offers evidence that demand planners can set extended lead times for 10 days or sooner to provide more accuracy delivery promises to customers.

Furthermore, demand planners can gain even greater insight by viewing frequency distributions for shortage recovery times broken down by individual commodities. For instance, if a demand planner only manages motherboards or hard drives, he or she will likely only want to see the distribution of recovery times for those specific commodities. Figure 12 below displays recovery time frequency distributions for several commodities, all with similar yet slightly different patterns in recovery.

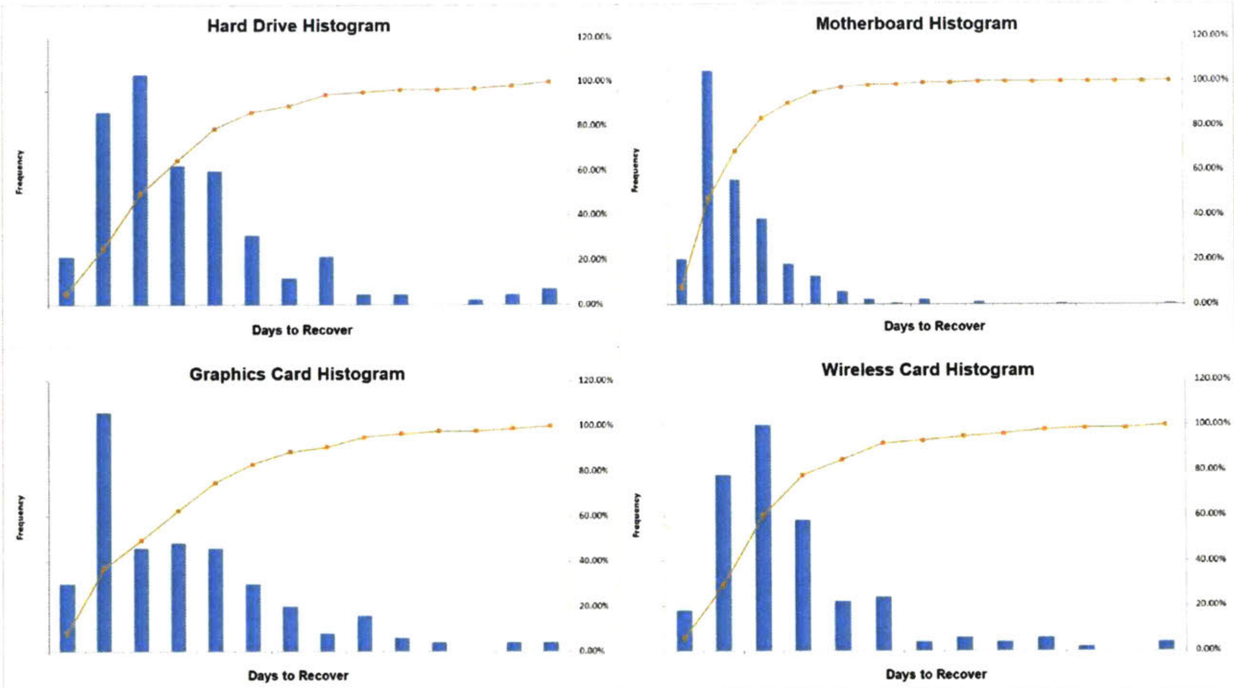

Figure 12. Frequency distributions for recovery time broken down by example commodities

Past recovery times do not necessarily indicate that future recovery times will behave similarly; nonetheless, a frequency distribution of all part recoveries offers an added layer of intelligence for when demand planners must extend lead times without knowledge when shortages will recover.

4.4 Smarter Lead Time Adjustments

By analyzing extended lead time events in Dell's supply chain, several valuable insights can be used to improve how Dell's demand planners adjust lead times. First, as shown in Figure 10, larger volume shortages take on average shorter times to recover than piece part or single unit shortages. Likewise, Figure 11 highlights that approximately 80% of all inventory shortages recover within a ten-day period. Furthermore, demand planners can gain greater insight by viewing how specific commodities have recovered from past shortages. Unfortunately, with a limited set of data to analyze, it is challenging to accurately predict when a shortage will occur and proactively set lead times accordingly. Similarly, it is not possible to accurately predict what the exact correct lead time are required as shortages can occur for numerous reasons and each part can operate differently than similar parts. Despite these shortcomings, a statistical analysis of extended lead times can offer another level of intelligence to the lead time setting process.

One of the most effective ways this data could be used to improve Dell's lead time setting process is by understanding the mean, median, and mode of specific commodity recovery times. While simple, they are powerful tools to help demand planners better estimate recovery times when the replenishment time is unknown. Table 3 below displays a list of crucial commodities in Dell's supply chain and their corresponding values for days to recovery.

Commodity	Mean	Median	Mode	95th Percentile
Commodity 1	5.1	4	2	12
Commodity 2	8.6	5	2	27
Commodity 3	11.4	7	14	32
Commodity 4	8.0	5	1	23
Commodity 5	7.2	4	1	24
Commodity 6	9.7	7	4	25
Commodity 7	10.3	6	3	29
Commodity 8	7.8	5	2	28
Commodity 9	4.7	4	4	10
Commodity 10	6.2	5	1	17
Commodity 11	7.1	5	2	22
Commodity 12	7.2	5	1	20
Commodity 13	5.1	3	2	15
Commodity 14	5.7	4	3	17
Commodity 15	9.4	6	2	34
Commodity 16	9.6	7	7	28
Total	7.5	5	2	24

Table 3. Days to recover for shortages of listed commodities over a six-month period

While these values may seem simplistic, for a demand planner with no insight into when Commodity 11 will recover from a shortage, he or she can possibly decide to set the extended lead time for Commodity 11 to the mean recovery time, which would be 7 days according to Table 3. The demand planner may also, exercising judgement on the situation, set the extended lead time to the mode, or most frequently occurring recovery time, which would be 2 days for Commodity 11. The 95th percentile value for recovery times is a valuable number to know because it sets the number of days for when 95% of all shortage events recovered by. If demand planners were overly conservative, they could set the lead time higher to prevent certain orders from being late. The unintended consequence of being conservative is that it leads to orders arriving to customers earlier than promised. The benefit of referencing the mean, median, and mode values for recovery times is that demand planners can have an added layer of intelligence for how certain commodities have recovered in the past. And if the mean, median, and mode values are less than what they think the lead time might need to be, demand planners can set the lead time lower than they would have otherwise.

The goal of a statistical analysis of extended lead time events is to yield insights into how parts recover in Dell's supply chain and add intelligence to the lead time setting process. By combining the insights made from understanding the inverse relationship between volume and recovery time as well as the distribution of recovery times across commodities, demand planners have more resources to improve how they ensure customers are getting as accurate delivery promises as possible. To improve the lead time setting process even further, demand planners can request more data regarding suppliers for the specific parts they managed. For example, if Part X was supplied to Dell by Supplier Y, the next time Part X goes short, the demand planner can set the extended lead time of Part X to Supplier Y's maximum supplier process time. That is, if the demand planner knows how quickly Supplier Y can manufacture and ship the Part X to Dell, the demand planner should set the extended lead time to the maximum supplier process time. This, along with a firm understanding of part recovery times in Dell's supply chain, would provide demand planners a solid foundation for setting accurate and precise extended lead times.

Conclusion and Future Work

The motivation of this project was to find ways Dell could improve the accuracy of its on-time shipment commitments to its customers, whether it be by finding ways to set proactive lead times or improve the accuracy of extended lead times. Problems with lead time accuracy can best be described as "symptom of a problem"; for instance, the first problem was that a specific part for a customer order was not on-hand when the order entered production, the order was delayed, and the lead time promised to the customer was inaccurate. Similarly, unplanned changes to customer orders or problems with information technology systems can cause orders to be delayed in processing through production and, as a result, promised shipment times will be missed and customer experience will suffer. The goal of this project was not to fix those initial problems, but rather knowing that these problems will occur, finding a way to determine when extended lead times are needed and what extended lead time should be set. Dell has a large and complex supply chain network to meet its customer and business needs; and with any large and complex supply chain, Dell must balance the tradeoffs between increasing delivery time competitiveness and with decreasing variability of products and parts. This chapter will discuss the conclusions and recommendations for how the work described in this thesis can be applied, what the relative impact to Dell can be, and where further work is required.

5.1 Recommendations

While exploring how Dell can find predictive ways of adjusting lead times, several areas of improvement have been identified for how Dell can continually improve its on time delivery commitments. No matter how Dell decides to structure its supply chain, it will always have to balance certain tradeoffs such as: reduced costs of outsourcing manufacturing versus lack of visibility into production facilities; or offering more product options to customers versus having large volumes of inventory. Efforts to improve lead time setting face similar tradeoffs, such as trying to balance setting correct lead times with inherent uncertainty in the supply chain. Despite the uncertainties, the motivation for the project was how to make improvements to Dell's lead time process and, ultimately, improve customer experience. With this improvement effort, several recommendations are put forth in the following paragraphs for how Dell can implement and improve the results of this thesis as well as investigate further areas of opportunity.

First, it is recommended that the demand planning team adopts using the deterministic method for identifying inventory shortages while not replacing any other internal processes. While the deterministic method is roughly 85% accurate for identifying part shortages and recommending extended lead times, it can be used in tandem with other systems and processes for adjusting lead times. The benefit of immediately incorporating the deterministic method with current processes is to assist in decreasing human error of missed and late lead time extensions. Demand planners can easily input the part numbers they want the model to test, run the model which automatically pulls the required data from Dell's information technology systems, checks them according to the rules and assumptions of the model, and it outputs a list of parts that are currently short or will go short within the next two weeks. As demand planners have competing demands, they often struggle with adequately checking all their parts every day to check if any of their lead times need to be adjusted. The deterministic model simplifies the process, at least for testing against part shortages, so the demand planners can check parts from a short list (such as 25 parts) instead of checking all parts they are responsible for (which can be upwards of 200 parts). Furthermore, it is recommended the demand planners incorporate the results of the statistical analysis of extended lead time events into their internal processes. The deterministic method is useful for identifying the parts that currently need or will need extended lead times; however, if the model does not see an inbound supply in the next two weeks, it will not be able to recommend an accurate extended lead time. This is when demand planners will need to reference the statistical analysis of part recovery times. By combining the deterministic method and statistical analysis of recovery times, demand planners can quickly identify parts requiring extended lead times and find the most appropriate lead tine to set. Additionally, combining this research with existing Dell processes, the model can be run with existing automation software to further eliminate burdens on demand planners and managers.

Second, it is recommended Dell invests to improve its data collected at the part level. As Dell has a robust order level tracking system, the company could stand to benefit from more rigor behind part level tracking and data collection. For instance, it is challenging to aggregate data more than a few weeks old and there are opportunities for more granular time bucket data storage. Additionally, parts in Dell's supply chain typically have a life span of only 12 to 18 months (i.e. how long the part is used in the production of Dell products). This adds an additional layer of difficulty for analyzing specific parts in Dell's supply chain. A certain part may only go short once or twice in an 18-month period. If there is no connection to previous parts or what parts replaced other parts, it becomes difficult to gather large sets of data on specific parts to analyze for patterns and trends. If Dell were to begin collecting historic inventory levels in more granular time buckets, it would be easier to measure how accurately supply met actual and forecasted demand. If this database were robust and comprehensive enough, planners could test how certain parts have performed over long periods of time and if there were any patterns that predict extended lead time events. With a thorough part level database, Dell could unlock hidden sources of potential for improving lead time accuracy through daily phasing profiles or advanced analytics.

The third recommendation of this thesis is to invest in business systems in addition to investments in information technology. As discussed in the literature review of this thesis, the *business process dilemma* occurs when firms only invest in technology but not corresponding business units or processes to incorporate or fully utilize the new technology. For example, if improved information technology systems, such as real-time inventory level tracking, are implemented for part level lead time setting, demand planner functions can be automated as the system could adjust lead times in real time. Investing in the real-time inventory tracking but maintaining the same business processes could lead to duplicated efforts, unaligned performance metrics, and hinder performance. If Dell decides to invest heavily in improved data collection and management systems, it will need to test new business processes, eliminate old functions, and potentially restructure planning systems and job functions. Current lead time setting processes operate at roughly 80% to 85% accuracy accounting for current challenges documents in this study. If Dell strives to achieve 95% or higher on-time delivery performance and proactive lead time setting, it is recommended Dell improves information technology systems while simultaneously investing in and experimenting with new business processes, polices, and procedures based on the needs of the business.

5.2 Impact to Dell

Like many organizations with their own supply chains, Dell is working to find new ways to improve its on-time performance while still offering many high-quality products to an expanding customer base. This research project was one effort in Dell's quest to improve lead time setting accuracy. If Dell were to implement the results of this research immediately, there would be few negative impacts on daily operations as the deterministic model can be easily incorporated into daily processes of the demand planning team. There will be no increases in time spent maintaining systems, expenses in upkeeping the deterministic model, or costs in changing underlying data structures. As stated earlier, the initial benefit of starting to utilize the deterministic model will be the reduction of human errors associated with adjusting lead times and execution speed of identifying extended lead time parts. The deterministic model will offer a roughly 3% improvement over current processes, specifically by decreasing the amount of missed and late lead time extensions.

The deterministic model was designed using parts and data from Dell's North America distribution system, which is also the region the model was tested on. When the model was tested using data from Dell's Europe production and distribution database, the process, in its current form, was deemed incompatible with the region's part level data structures and processes. Upon further analysis, the cause of this error was due to structural differences in how data is stored across different regions in Dell's supply chain. Project timelines limited the feasibility of constructing a new model tailor designed to Dell's European systems. With these structural differences, the deterministic model cannot be easily scaled across regions without altering the structure of the tested model. Likewise, the model was developed by looking at several specific commodities in Dell's client consumer business, which has relatively steady demand over the year. Scaling the model to cover commodities from Dell's retail business would likely require restructuring the mechanics of the model to account for retail sales and procurement cycles or seasonality demand changes. As Dell continues to improve its data collection and management systems, the deterministic model can be incorporated into systems to automatically track and update lead times resulting from part shortages. Lead times could then be automatically adjusted to when replenishment supplies are scheduled to arrive. Eliminating the need for demand planners to manually track part shortages and adjust lead times would free resources from the demand planning department to address other challenges hindering on-time delivery performance.

5.3 Impact to Industry

The supply chain industry has changed significantly over the past two decades. What had traditionally been a costly and slow-moving sector has been transformed into area of strategic advantage for firms attracting customers that demand fast and timely delivery services. The definitions for what are competitive delivery times quickly change as customers demand more and want to pay less. Dell is at the center of this shift in supply chain competitiveness in the computer industry; and firms that find creative and innovative ways to improve their lead time accuracy can achieve advantages over competitors in the same category.

Many firms delivering goods to end-user customers often face problems with ever increasing inventories spanning across different regions, often from hundreds of different suppliers, all to different production locations, and shipment destinations. To quickly address these problems while not having to disrupt operations, manual labor often is turned to as a fix to the problems. Unfortunately, the scale of problems can often be too large for individual or even teams of planners to adequately address every problem as they arise. The framework of the deterministic model and statistical analysis are simplistic yet powerful. If firms can quickly identify, at any point along their supply chain, where an inventory shortage is occurring or will soon occur, those firms can adjust lead times accurately. The model framework is robust enough to monitor potentially thousands of parts of both low and high-volume mixes.

Furthermore, the statistical analysis explained in this thesis is an area where supply chain firms can begin discovering valuable insights into how parts behave in their supply chains. While this research only explored how parts in Dell's supply chain recover from shortages, historic performance data of parts can yield untold insights into how a firm's supply chain operates. Armed with a robust enough data set and advanced analytics techniques, firms can find hidden trends and patterns in their supply chains that they can leverage improvement efforts on. For example, the statistical analysis of part in Dell's supply chain discovered that 80% of part shortages often recover in less than 10 days. This insight can help adjust policies and procedures for how lead time are adjusted when there is no replenishment order visible in the data. Using big data and machine learning techniques, firms will continue to raise the standard on what defines a competitive supply chain.

5.4 Future Work

One area for continued work on this project would be to repeat the testing period of the deterministic model using different commodities and across a different region. Conducting this work would identify further sources of error in the model and where structural changes need to occur both with the deterministic method and within data management systems at Dell. To conduct this work, close collaboration would be required amongst Dell operations team operating in their respective regions. This analysis would also yield if other methods to proactively manage lead times in different regions would be more effective than a deterministic method.

Another area of opportunity for how Dell can proactively manage lead times would be an analysis on how Dell can accurately measure the impact of lead time adjustments. A key shortcoming identified during this research project was the lack of ability to see how an adjusted lead time had an impact on a specific order. As Dell manages most of its systems at the order level, the connection to the part level lead times and order status can be difficult to connect. This disconnect makes it challenging to adequately measure how adjusting a specific lead time impacts specific customer orders. For demand planners, beyond the data currently available for the part they are managing and whatever intuitive knowledge they have, demand planners are making their best estimations for what an extended lead time should be as they cannot adequately measure their impact on customer orders. This area of research could detail how much Dell could benefit by expanding its robust tracking of order to incorporate more part level tracking. Current structural limitations in Dell's order and data management systems would hinder this research; however, if a research project could create a clear connection between part, commodity, and order level data, strategic and tactical supply chain decisions beyond could be made holistically.

Another opportunity for improvement would be a statistical analysis of end-of-life and low-use parts in Dell's supply chain. Through the course of developing and testing the deterministic method, other sources of error that skewed results were often parts that had reach their end-of-life in Dell's supply chain and parts that had low usage. Like many firms, Dell must make tradeoffs between offering customers a wide variety of options and products versus decreasing inventory and increasing competitive delivery times. As parts are constantly changing to account for changes in technology and customer needs, Dell has many low-running parts that sometimes impact planning and order production. Research into determining the impact end-of-life parts have on customer orders as well as how to predict when the end-of-life will occur could offer improvements on-time delivery performance. With further developed data sources, research could identify low-volume parts that have disproportionally high impact on customer orders and lead times could be adjusted proactively.

A strong area for opportunity would be to run a pilot program of setting lead times based on a Random Forrest or Decision Tree analysis. For this to be accomplished, Dell would have to improve the data volume and specificity for a specific number of parts. For example, if Dell were to monitor only Commodity X but monitor it in greater detail (i.e. more data volume) such as supplier name, supplier location, timestamps of arrival, and so forth. This would require, at least for the piloted parts, the changes to data systems mentioned earlier: being able to draw a connection between part level and order level data, more robust historic supply data, and transparency to the daily level of data. Attempting to run machine learning algorithms on current part level data at Dell is not optimal due to the small amount of data available as well as the limited categories of data (such as only demand forecasted, actual sales, and backlog are readily available). If a machine learning algorithm utilizes a large and robust data set, a Random Forrest or Decision Tree could classify what an appropriate lead time for a part in the pilot program could be. With this pilot program, it may be possible to also analyze what factors precede extended lead time events.

A final and possibly very interesting area of analysis for improving lead times in Dell's supply chain would be a thorough analysis of supplier process and transportation times. When a part is identified as short in the deterministic model, it automatically looks to when the next resupply time will be and recommend that as the extended lead time. Unfortunately, if the next resupply time is unknown (either not in the data or not planned), the model recommends to the demand planner to set the lead time greater than 14 days. Next, the demand planner must rely on the statistical analysis of recovery times and intuitive knowledge to set the extended lead time. However, if the max supplier process and transportation time for that part was known, the demand planner can set that as the extended lead time. This analysis could be conducted over different part suppliers to Dell based on the parts provided, quantity, location, and so forth. This analysis would require transparency into Dell's suppliers, and it could offer further improvements to the accuracy of lead time and delivery commitments.

Bibliography

Angkiriwang, Reina, et al. "Managing Uncertainty through Supply Chain Flexibility: Reactive vs. Proactive Approaches." *Production and Manufacturing Research*, vol. 2, no. 1, Taylor & Francis, 2014, pp. 50–70, doi:10.1080/21693277.2014.882804.

Bendul, Julia, and Mathias Knollmann. "The Lead Time Syndrome of Manufacturing Control: Comparison of Two Independent Research Approaches." *Procedia CIRP*, vol. 41, Elsevier B.V., 2016, pp. 81–86, doi:10.1016/j.procir.2015.08.104.

Bhatnagar, Rohit, and Amrik S. Sohal. "Supply Chain Competitiveness: Measuring the Impact of Location Factors, Uncertainty and Manufacturing Practices." *Technovation*, vol. 25, no. 5, May 2005, pp. 443–56, doi:10.1016/j.technovation.2003.09.012.

Childerhouse, P., and D. R. Towill. "Analysis of the Factors Affecting Real-World Value Stream Performance." *International Journal of Production Research*, vol. 40, no. 15 SPEC., 2002, pp. 3499–518, doi:10.1080/00207540210152885.

Dell, Michael, and Catherine Fredman. *Direct from Dell: Strategies That Revolutionized an Industry*. HarperBusiness, 2000.

Hegedus, M. G., and W. J. Hopp. "Setting Procurement Safety Lead-Times for Assembly Systems." *International Journal of Production Research*, vol. 39, no. 15, 2001, pp. 3459–78, doi:10.1080/00207540110061625.

Oláh, Judit, et al. "Future Challenges and Areas of Development for Supply Chain Management." *Scientific Journal of Logistics*, vol. 14, no. 1, 2018, pp. 127–38, http://www.logforum.net/pdf/14_1_11_18.pdf.

Selçuk, Bariş, et al. "An Explicit Analysis of the Lead Time Syndrome: Stability Condition and Performance Evaluation." *International Journal of Production Research*, vol. 47, no. 9, 2009, pp. 2507–29, doi:10.1080/00207540701420552.

Simchi-Levi, David. *Operations Rules: Delivering Customer Value through Flexible Operations*. The MIT Press, 2010.