Modeling End-to-End Order Cycle-Time Variability to Improve On-Time Delivery Commitments and Drive Future State Metrics

By

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Submitted to the MIT Sloan School of Management and the Institute for Data, Systems, and Society in partial fulfillment of the requirements for the degrees of

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Abstract

Dell is accelerating investments to simplify and improve one of the core competencies it was founded on, customer experience. One goal within this initiative is to increase the percentage of orders that are on-time to a committed Estimated Delivery Date (EDD). EDDs for products vary greatly with the complexity of the customer purchase orders. In order to remain competitive, Dell has set an aggressive goal to provide better on-time delivery performance. Dell needs to quote more accurate lead time commitments to customers and increase the stability of high variability steps in the end-to-end order supply chain.

The EDD lead time, from customer order to proof of delivery, consists of a payment (processing) phase, manufacturing (build, inbound logistics, warehouse) phase, and a logistics (delivery) phase. Each of these segments are managed by different organizations within Dell. Understanding what the end-to-end future state looks like will allow functional teams to set improvement targets to achieve Dell's on-time goal.

This study has three main objectives: (1) determine the key drivers of variability in the current state process, (2) identify opportunities for more detailed EDD range generation, and (3) quantify targets for individual process steps to drive towards the target future state. Three high volume Build to Order (BTO) regional product lines were chosen as cases to analyze. BTO product lines, compared to Build-to-Stock (BTS), inherently have a more variable supply chain for the processes examined.

To meet the main objectives, this thesis examines the hypothesis that a simulation model based on historic order data can be used to quantify existing cycle time performance in the supply chain and deliver targets to achieve Dell's on-time performance target. Key drivers of cycle time variation were identified through process mapping and design of experiment statistical analysis.

Results from the modeling and sensitivity analysis produced actionable recommendations for each of the three objectives and lead to a pilot project to improve EDD commitments for an existing desktop product line. Direct to customer shipping, inbound logistics method, and day of week were identified as attributes that were significant drivers of variability and were underutilized in the EDD commitment process. This provided an opportunity for smarter lead time setting. A pilot project for a desktop line adjusted lead times to incorporate direct to customer shipping and day of week, resulting in a 30-40% on-time performance improvement. Finally, modeling results quantified cycle time distribution targets for each process step to achieve Dell's future state goal for on-time delivery. Dell is building on this project by analyzing more regional product lines and exploring opportunities to incorporate machine learning.

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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

In 2013, Michael Dell, along with Silver Lake Partners, took Dell Inc. private to re-focus the company's long term strategy without the quarterly scrutiny of Wall Street. One of the strategic areas of investment for the private company is to accelerate the delivery of an enhanced and simplified customer experience (Company Herritage, n.d.). One year after privatization, Dell created the End to End Order Experience Program. This program is tasked with increasing the percentage of products delivered on-time to a targeted best in class level. The goal of this project is to investigate variability in the current state supply chain and improve on-time delivery accuracy.

1.1 Motivation

The motivation for this project came from understanding current state performance and delivery lead time commitment processes. The order process for products is split into three high-level sequential phases: payment, manufacturing, and logistics. Each of these phases has historically operated in a silo and determined their portion of the total lead time committed to the customer. For nearly all customers, a late order is a bad customer experience. The culture throughout the supply chain put a strong emphasis on not being late to each phase's lead time allocation. The "don't be late" mantra led to conservative delivery forecasts that would ensure limited late orders. As a consequence, delivery commitments became conservatively long and many orders would ship to customers much earlier than the commitment. Some consumers may not mind an early shipment, but for others it is just as inconvenient as a late shipment. Corporate customers with large orders may not have storage space for deliveries before the committed date range. For individual consumers, packages could be left on doorsteps for several days increasing the likelihood of theft or damage.

During checkout, Dell communicates an expected delivery range to the customer based on several factors known prior to final order entry. Among these factors are payment method, product type, customer location, shipping method, and component inventory. Orders with similar factor characteristics are grouped together to create cycle time distributions for each of the three process phases. Trends in distributions are monitored over time, and each process phase calculates a lead time based on recent history, allowing for up to five to ten percent of orders to be later than the commitment. By using recent history, Dell is able to capture incremental improvements in processes within supply chain phases. However, using recent history ignores seasonal drivers of variation in processes. Extreme deviations from business as usual operations can skew recent history, so Dell carefully examines the drivers of abnormal operations.

Figure 1 illustrates this lead time determination for an example product's manufacturing phase. A six business day lead time commitment allows for no more than five percent of orders exceed the commitment. Choosing a lead time lower than six business days would cause an unacceptable percent of orders to exceed the commitment. Conversely, a lead time of more than six days would have less orders late to the commitment, but could contribute to a total delivery range commitment that is not competitive to industry peers. The lead times for each phase are then added together to calculate the last day of the delivery commitment range.

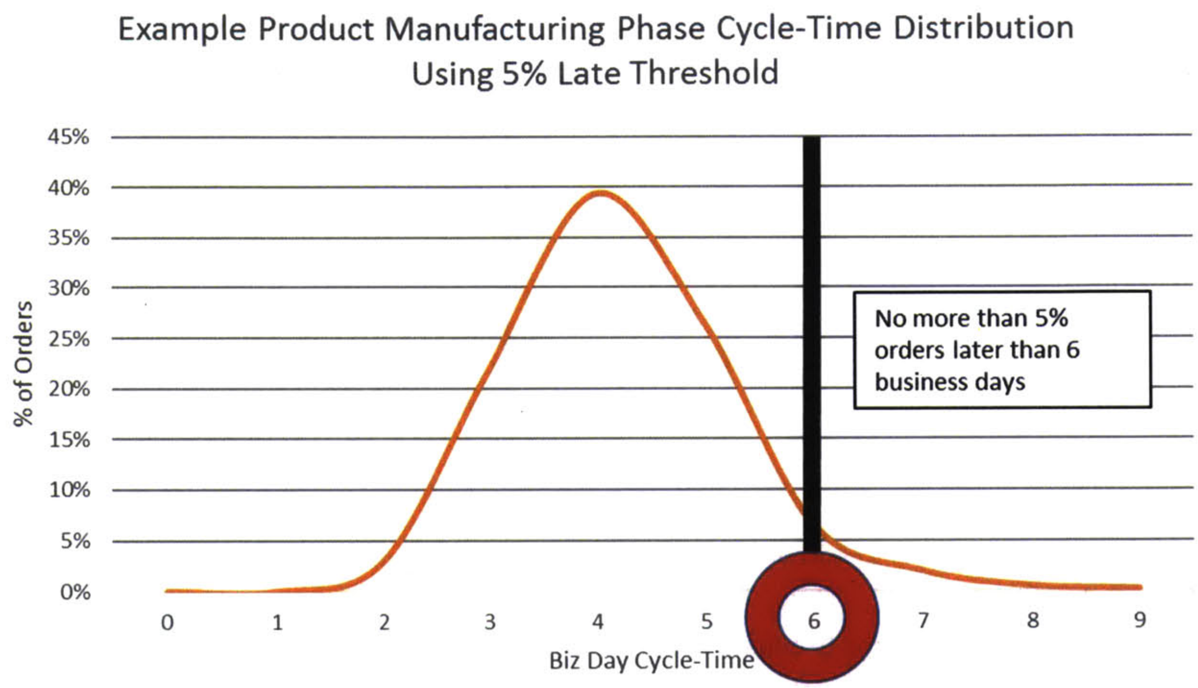


Figure 1: Manufacturing phase cycle time distribution and lead time determination allowing for up to 5% of orders to be late to commitment.

If the lead times for payment, manufacturing, and logistics were one, six, and three respectively, the summation of these, ten business days, would determine the last day of the delivery range. After determining the last day of the delivery range, Dell applies a competitive framework to determine the first day of the delivery commitment range. The competitive framework calculates the length of the delivery range taking into consideration industry peer benchmarking and historic Dell cycle time performance. Figure 2 illustrates an example of how the delivery commitment aligns to the distribution of actual end-to-end order cycle times. This example is for an order that has a combined last day lead time of ten business days and may have a competitive delivery range of four business days, making a final delivery commitment to the customer of seven to ten business days. A delivery with a shorter last day lead time, such as five business days, may only have a delivery range of three days, making a final delivery commitment of three to five business days.

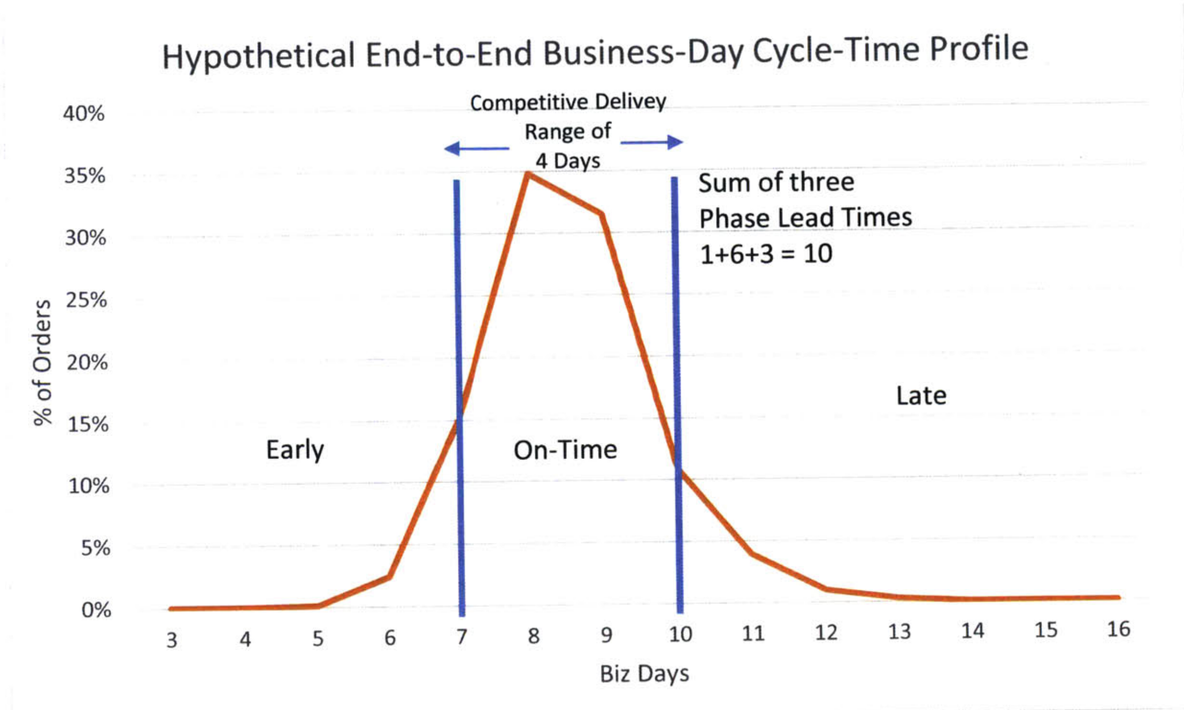


Figure 2: Hypothetical on-time commitment example, allowing for Up to 10% late orders, plotted against actual order cycle times

Each phase commits its lead time to equal a specified high percentile of recent cycle time distributions and all three phases are added together. If the goal is to have on-time accuracy equal the same specified percentile used to calculate lead times, Dell is assuming the three process phases are not independent. The summation of individual lead times implies that an order that is late to the payment commitment will also likely exceed the manufacturing and logistics commitment allocations. This assumption could cause orders to have unnecessarily long delivery range commitments if process phases are actually independent from one another. An end-to-end commitment process, instead of three phase, could provide a more accurate delivery window and increase on-time delivery performance.

Actual order performance using the three phase commitment process is illustrated in Figure 3 for an example US customizable product line that is representative of the performance of the entire US customizable product portfolio. Dell stakeholders view on-time performance through similar charts on a weekly basis. This graph highlights the percentage of early, on-time, and late orders for a twelve-month period. Over the past year, the Order Experience Program has on average made about a 10-point gain in on-time order delivery, but about

30% of orders remain delivered early to the committed delivery range. Current state on-time performance is still far short of the future state goal.

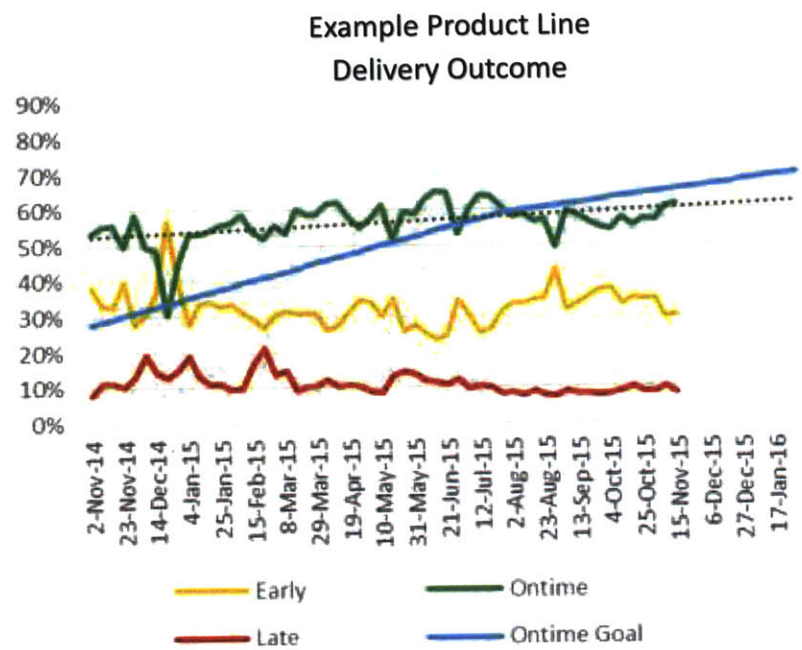


Figure 3: Example delivery accuracy trend chart for an average customizable product line.

1.2 Objectives

This project has three main objectives to help Dell increase on-time delivery performance. The first objective is to identify the key drivers of variability in the current state process. Each order has many characteristics that could influence the amount of time spent in each step of the supply chain, but Dell does not currently examine the impact of all characteristics on the delivery date commitment process. Identifying impactful and unutilized order characteristics can help Dell determine where to concentrate investment resources to improve cycle time performance and the delivery date range commitment process.

Bridging the gap from the current state to the aggressive future goal state requires investments in both the lead time calculation engine and operational processes. The second objective is to find opportunities for Dell to provide more detailed and accurate delivery date range to the customer. Recommendations for changing the delivery date commitment must maintain a competitive offering compared to industry peers. This means a recommendation to simply provide a much wider delivery date range to improve on-time performance would not be feasible.

The other option to improve on-time delivery is to reduce variability in the underlying supply chain processes. The third objective of this project is to quantify future state cycle time performance targets for each step in the supply chain. Dell's supply chain measures and sets metrics to improve cycle time performance throughout the supply chain. The current state continuous improvement approach has led to incremental improvement to on-time delivery performance. This third objective would provide Dell cycle time performance targets for a future state supply chain that would meet the company's on-time delivery performance goal.

Senior management engagement is also critical to successfully implementing change in the supply chain and delivery date range commitment processes. "Customer experience does not improve until it becomes a top priority and a company's work processes, systems, and structure change to reflect that." (Meyer & Schwager, 2007). The objectives of this project provide data driven recommendations to help Dell senior leadership understand how the future state supply chain should perform and commit to the customer.

1.3 Hypothesis

This project hypothesizes that variability can be better understood by creating a modeling framework that statistically identifies key drivers of variability and uses simulation to predict the amount of time orders spend in each step of the end-to-end process. The modeling framework needs to be granular enough to provide meaningful improvement targets to each functional process. The framework must also be flexible enough to address the uniqueness of regional supply chains, incorporate process improvements, and accept new processes not currently operational.

Another approach examined for this study was to identify drivers for variability by flagging orders that did not meet ideal state supply chain performance. Orders not meeting ideal state expectations would be separated from the population and examined for similar attributes. This analysis would provide insights into the causes of variation in the supply chain and could be used to create more detailed improvement targets for supply chain process steps. In 2014, Tracy Napolilo created a framework for Nike that could be tailored to the Dell supply chain to accomplish this approach (Napolillo, 2014). Unfortunately, this approach would not directly address the second objective of this study, to improve delivery date range commitments.

A third approach considered for this project was to identify key drivers of variability and create a regression model to forecast end-to-end cycle times of future orders. This approach would consider the start and end points of the order process instead of analyzing each individual process step, producing a simpler model that is easily repeatable and can accommodate more historic data. This high level regression approach would provide insight into key drivers of variability and opportunities to improve end-to-end delivery date range commitments. However, this approach would not offer enough insight into the individual processes to meet the third objective of this project, providing performance cycle time targets to supply chain processes.

1.4 Thesis Outline

Chapter two of this thesis discusses the research analysis used for this study. This chapter explains why a flagship build to order (BTO) notebook product line was chosen for this study and the current state processes included in its supply chain. The chapter then describes the methods used to statistically screen for and confirm with Dell stakeholder the order attributes that drive cycle time variation at each step of the supply chain. Outputs from this section address the first objective of this study, identifying the key drivers of variation in the supply chain. Statistical analysis of the correlation between process step cycle times is also examined to validate the assumption that processes are independent from one another.

Chapter three uses the significant attributes for each process, identified in Chapter two, to construct process flow branch diagrams that represent different order flow paths for the current state supply chain. Then, the chapter describes how the process diagram branches were used to parse the historic order dataset and fit distributions to the process step cycle times. These cycle times were then applied to a simulation model to forecast the end-to-end cycle times for each branch of the process flow diagrams. Results from the simulation were then calculated into business performance metrics used by Dell and validated to historic data.

Chapter four highlights the opportunities to address the second and third objectives of this study, improving delivery date range commitments and providing future state cycle time metrics for individual process steps. Examples are used to illustrate how using statistically significant criteria not currently used by Dell's delivery commitment calculations can improve on-time performance. Specific standard deviation reduction targets are then calculated to illustrate how a future state supply chain should perform to meet Dell's aggressive on-time goals.

The fifth chapter applies the modeling framework to a flagship BTO business desktop line. The chapter explains why this product line was chosen and highlights how the framework was used to build a simulation model. The simulation model outputs revealed an opportunity to commit more aggressive delivery date commitments for directly shipped orders and to increase the percent of on-time orders by 39%.

The final chapter discusses how the recommendations from using the modeling framework were received by Dell and the main lessons learned. This chapter also discusses how this framework can be applied to other industries and future work that can build off of this modeling framework.

1. Research Analysis

2.1 Regional Product Case Approach

Dell is estimated to have shipped over 10 million PCs in Q4 2015 globally, accounting for approximately 13% of the market (Pettey, 2016). With many SKUs and regions, it was necessary to determine a subset of the order population for the initial analysis. Generating a leaner dataset required collaboration between the data analytics team, the order experience team, and the operational leadership teams. This study focusses on two flagship notebook and desktop build to order (BTO) US products. The notebooks selected are manufactured in Asia, while the desktop line is manufactured in Mexico.

To reduce complexity of Dell's end-to-end product order supply chain, regional products were chosen as an example of the broader supply chain. Deciding on these two offerings involved discussion with regional Order Experience program team leaders, data analytics team members, and operational function managers. Prior to this study, each stakeholder had preferences for areas of focus where the supply chain is most variable. In general, stakeholders were in alignment and expected most of the end-to-end process variability to be in the inbound logistics and Dell consolidation facility steps, both of which are managed by third parties. The standard offering for inbound logistics from Asia to the US had a service window that was three days wide, which was almost as wide as Dell's committed delivery range to the customer. For Dell fulfilment operations, a variety of services were performed on orders with little differentiation on the order delivery commitments. It was believed that because Dell creates delivery date range commitments allowing for a 5-10% threshold of late orders, less frequent processes with longer durations were setting the commitments for the entire order portfolio. Scoping the cases required regional products that flow through stakeholder focus areas. These areas included financing payment terms, orders that bypass Dell consolidation facilities, and premium outbound logistics.

The flagship configurable notebook product line, manufactured in Asia and delivered to the United States, was chosen to develop the initial framework. This line is the marque product for US business customers and constitutes the majority of order volume for the build to order portfolio. Business laptops come in many configurable models to suit the diverse business needs of Dell's end users. All models of the selected product line were used in this study, but limited to the main production facility in China. The product line has approximately eighty thousand orders per quarter, approximately half of total US build to order volume. On-time performance is measured by the order and not weighted by the number of systems that are in the order. This means that an order for one notebook counts the same as an order for 25 or 50 notebooks for on-time performance. The most recent month available at the time of this study, August 2015, was chosen for the order dataset.

The other important characteristic of the case study design for this analysis was limiting the data to business as usual (BAU) operations. One component of obtaining a BAU dataset was to eliminate orders that did not receive a standard manufacturing lead time commitment during customer check out. Dell has product specific lead times for many of the process steps within the manufacturing phase. Orders that do not meet standard lead time commitment criteria typically had forecast delays due to component inventory shortages and varied in duration based on SKU and inventory levels. Only 5-15% of orders from case studies observed do not meet standard lead time criteria. Other non-standard events could also impact the BAU operations. During a two-week period in June 2015, extreme thunderstorms near the Nashville consolidation facility cause abnormal logistics delays, skewing cycle times in preliminary data analysis. To maintain a BAU order population, orders impacted by events like these would also require exclusion from the modeling framework.

2.2 Current State Processes and Data Availability

The current state processes for configurable US notebooks span from payment to delivery. The order system is broken up into three phases named payment, manufacturing, and logistics. Within these three phases are seven sub processes that are separated by timestamps. Payment and outbound logistics each have one of these seven sub processes. The remaining five sub processes, network planning, facility planning, build, inbound logistics and consolidation, are in the manufacturing phase. An order must complete the previous process step to move on to the next. Because the temporal data for the seven sub processes are separated by timestamps, it is important to understand the boundaries of the processes in relation to these timestamps. To maintain a comparable end point of the system, the delivery's first attempt was considered the end of the process. Orders delivered on a subsequent attempt were noted in the data, but for this study orders were considered completed on the first attempt. Figure 4 illustrates the process phase flow and the action that creates the timestamp that ends each step in the dataset.

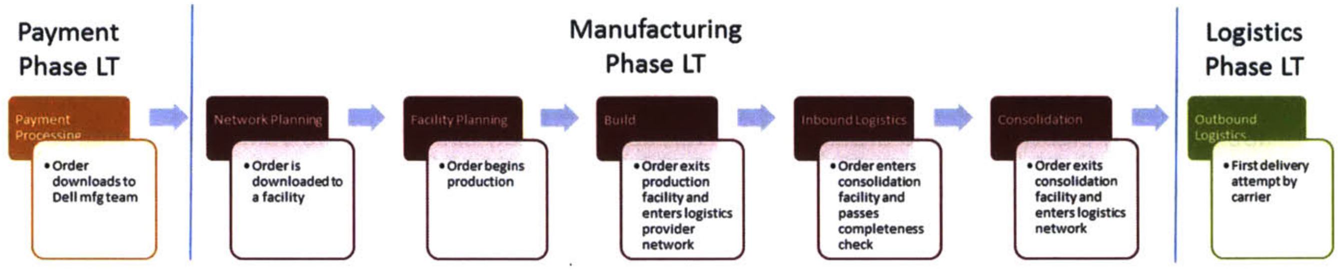


Figure 4: Order experience supply chain process flow with descriptions of the actions that create process ending timestamps

Previous efforts at Dell merged significant data related to order experience from several databases into one. This combined database includes order characteristics that determine the process flow and lead time commitment through payment, manufacturing, and logistics. Actual lead time commitments and process step timestamps for each order are also included.

Each one of the three phases is responsible for a portion of the lead time for each product. Lead times are committed based on order characteristics that are known at the time of order entry. For example, in payment, paying with a credit card will have a shorter lead time compared to creating financing terms. Generally, both payment and logistics lead times are determined agnostic to the manufacturing phase processes, so a notebook, tablet, or mouse would follow the same lead time commitment logic for these two phases.

In the current state, all of the processes within manufacturing have characteristics that can impact the lead time commitment for any product. These include component inventory, build facility, inbound logistics method, and consolidation services. Most of the criteria in manufacturing is product specific.

The order flow begins with the payment processing phase. An order will not continue to the manufacturing phase until the payment is validated by an exception based process. Order criteria such as payment method and customer type impact the approval process and therefore the cycle time performance of this process. For this study, only payment methods of credit card, gift card, and financing terms were incorporated. These payment terms represent over 80% of the order population. Payment terms that were excluded for this analysis include wire transfer, lease terms, credit terms and orders that qualify for Dell's Buy and Try program.

Once payment terms are validated, the order moves into the manufacturing phase. The first two steps in manufacturing are planning-related. Network planning is the time an order spends waiting to be assigned to an original design manufacturer (ODM) facility. This is an automatic process that typically has a very short cycle time. Facility planning is the time spent in the ODM facility until the production of the product. Delays in this process step are driven by facility queue management and part shortages. Orders with known part shortage issues at order entry will receive an extended lead time commitment and were excluded from this analysis. Dell has a team continuously exploring opportunities in inventory management to cost effectively minimize part shortage events.

The next process step is building the product. ODMs operate within a negotiated service level agreement (SLA) that dictates cycle time and late tolerance. The SLA is unique for each product and facility. The build process represents a large portion of the total manufacturing lead time commitment. This process is considered complete after the order is completed and exits the ODM facility.

Once the order exits the facility, it enters the inbound logistics process. Lead time is influenced by the location of the ODM facility and the service level of transportation chosen. Inbound logistics has two unique paths determined by an order's need for additional value add services. Orders that do not require additional services can be directly shipped to the customer. Direct to customer shipments are shuttled from the ODM to a logistics carrier hub where they transition to the outbound logistics process, bypassing the consolidation step.

Orders requiring services are shuttled from the ODM to a Dell consolidation facility. Once the order is scanned and accounted for, it begins the consolidation process. Lead time commitments are based on the additional services required. These services include adding software, accessories, asset tags, specialty shipping labels, and other configuration services. The consolidation process is considered complete once scanned onto the appropriate outbound logistics carrier truck.

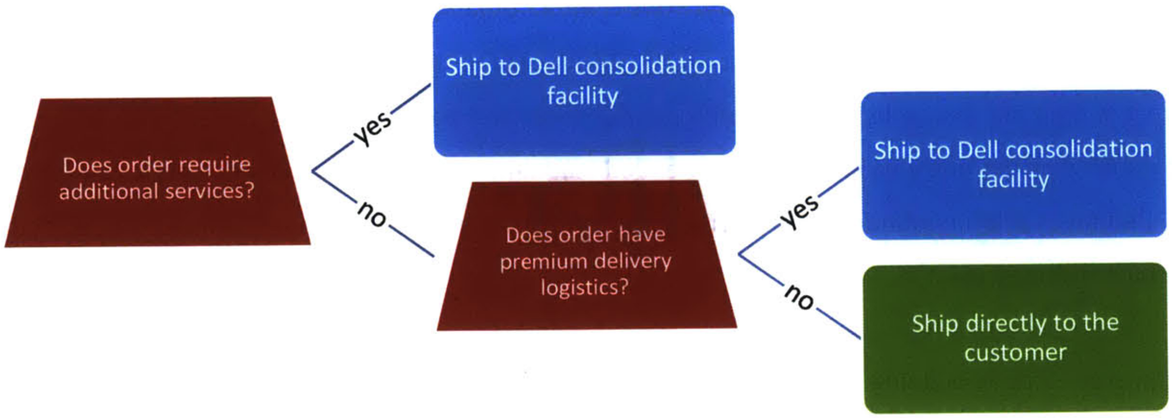


Figure 5: Decision tree describing simplified criteria to illustrate why an order is shipped directly to the customer or shipped to a Dell consolidation facility.

Outbound logistics begins when the order is in the carrier network. Dell uses multiple carriers to fulfil delivery demand. Lead times for this process phase are largely driven by customer location and delivery service. Only ground, next day, and second day delivery services, representing over 90% of the order volume, were included in this study.

Analysis of the current state and understanding how available timestamp data aligns with the processes gave insight into how the data would represent cycle time variability at the sub process level. Each process cycle time includes the handoff transition time to the subsequent process except for the production phase, which begins when production initiates and completes once loaded onto the truck for inbound logistics. Orders can spend time sitting on these trucks until the agreed upon cutoff time when the trucks leave the facility to begin transportation. Once the inbound logistics provider delivers the order contents to the consolidation facility, the timestamp does not initiate until the inbound logistics product is unloaded from the truck, unpacked, and all portions of the order are accounted for. Both of the handoff transition times discussed can also be impacted by the production facility, consolidation facility, and third party logistics provider's day of week schedule. Orders could wait an additional day in these transition states due to weekend work schedules or holidays.

Because inbound logistics timestamp data will include both of these handoff transition times, it is unlikely that the cycle times representing this sub process in the data will align to third party logistics providers service level agreement (SLA) hourly targets. These SLA targets begin at the agreed upon cutoff time when the trucks begin transportation and end once delivered to the consolidation facility. Dell stakeholder expectations are more aligned to the SLA targets than the actual cycle times represented in the data. Understanding what order characteristics impact these handoffs and the processes could explain variability in the end-to-end system.

2.3 Design of Experiment Statistical Screening

Current state analysis revealed that orders have many attributes that can impact how they travel through the supply chain. This chapter examines the portion of the modeling framework that determines the key order attributes that drive cycle time variability. Cycle time distributions of each process step are examined to determine the value of differentiating the order population to account for variation. Spending time analyzing extremely short duration processes, compared to the multi-day end-to-end cycle time, will not provide much value to the modeling framework. For processes where it is worth differentiating the order population, a design of experiment screening is used to identify order attributes that drive cycle time variation. The output of this portion of the framework will be a list of key attributes for each sub process that can be leveraged to segregate the order population into a process flow tree.

Configurable products have delivery date range commitments of at least five business days. Some of the sub processes, network planning and consolidation, have an average duration of under an hour. The duration of these two processes, compared to the total time it takes to flow through the supply chain, is not worth differentiating to account for variation. Payment processing is also a very short duration process compared to the end-to-end cycle time. However, internal Dell stakeholders were very curious about how attributes impacted the cycle time for different payment options, so attributes that cause variation were analyzed for this phase. Figure 6 shows the cycle time values by percentile for network planning, consolidation and payment. For consolidation, many orders arrive at the facility to only get a shipping label. Because of the sequencing of timestamp data creation, many of these get the arrival and departure timestamp simultaneously as they are loaded onto the outbound logistics truck, explaining the zero value for the percentile values up to 75%.

Payment Processing

Quantiles		
90.0%		3.048
75.0%	quartile	0.38
50.0%	median	0.22
25.0%	quartile	0.17
10.0%		0.12

Network Planning

Quantiles		
90.0%		0.37
75.0%	quartile	0.08
50.0%	median	0.07
25.0%	quartile	0.05
10.0%		0.03

Consolidation

Quantiles		
90.0%		12.78
75.0%	quartile	0
50.0%	median	0
25.0%	quartile	0
10.0%		0

Figure 6: Product line hourly cycle time distribution percentiles for payment processing, network planning, and consolidation process steps.

For the remaining four process steps, facility planning, build, inbound logistics, and outbound logistics, median cycle times ranged from 18 to 93 hours. These four processes made up the bulk of the end-to-end order cycle time. Figure 7 shows the hourly distribution percentile values of these processes.

Facility Planning

Quantiles		
90.0%		44.077
75.0%	quartile	24.87
50.0%	median	18.08
25.0%	quartile	14.15
10.0%		11.58

Build

Quantiles		
90.0%		45.679
75.0%	quartile	30.865
50.0%	median	22.32
25.0%	quartile	16.5
10.0%		13.35

Inbound Logistics

Quantiles		
90.0%		148.452
75.0%	quartile	118.9425
50.0%	median	93.35
25.0%	quartile	78.72
10.0%		63.27

Outbound Logistics

Quantiles		
90.0%		105.09
75.0%	quartile	83.93
50.0%	median	50.015
25.0%	quartile	34.84
10.0%		13.702

Figure 7: Product line hourly cycle time distribution percentiles for facility planning, build, inbound logistics, and outbound logistics process steps.

For the longer four process steps and payment processing, a design of experiment screening analysis was performed to determine which order characteristics, or combination of order characteristics, in the case study dataset are statistically significant. Another approach considered was to perform a stepwise regression to identify the criteria that drive the variability in the process. Stepwise regression tests one variable at a time and incorporates other variables if their addition to the set improves the R^2 of the model. The available dataset included over 70 independent variables of order attributes that could influence the cycle time performance at any of the seven process steps. Lists of the most impactful criteria for each process step are presented later in this chapter. Performing a stepwise regression with this many variables would be time consuming, and would not capture the potential correlation of independent variables. Also, the output of this analysis will be a list of significant criteria that will be used to create a product flow diagram. If the output were to create a linear regression model to forecast end-to-end cycle times, a stepwise regression would provide a useful solution.

It is important to note that certain characteristics are directly influenced by or provide similar information to another characteristic. For example, a certain SKU may by definition only have one production location and require additional services beyond the base model. SKU, and its inherent characteristics, would also drive the manufacturing lead time commitment. Using any of these related fields in addition to SKU in an analysis would be repetitive and could lead to double counting impacts. SKU however is an extremely granular attribute, and separating the order population based on SKU would not provide enough data points for this study's analysis. Attribute relationships were identified through interviews with stakeholders throughout the supply chain. It is important for this framework to be cognizant of these relationships when identifying statistically significant order features.

To screen the dataset for impactful criteria, the framework used the JMP effects screening platform. This platform is a least squares regression that relies on the sparsity-of-effects principle. This principle states that relatively few effects in a study are impactful and estimates based off of these effects would only provide random error (SAS Institute Inc., 2015). Effects screening was performed on each of the process steps individually, testing for first and second order relationships. An attribute was deemed significant if the individual p-value was less than 0.05.

For this analysis, a random sampling of 1000 observations from the filtered dataset of over 70,000 orders was generated to run through the screening module. Sampling and screening was repeated 10 times and then aggregated for each process step to limit sampling bias.

Once a sample of orders is generated, an individual process's cycle time, in hours, is selected as the dependent variable. All attributes are added as independent variables. For each potential predictive criterion, the null hypothesis is that the criterion does not add predictive value. As a result, any attribute that has a p-value of less than 0.05, a statistically significant threshold chosen for this analysis, would reject the null hypothesis and suggest that the criterion is significant to the model.

The outputs of this screening are Lenth t-ratio, individual p-value, and simultaneous p-value. Lenth t-ratio is a factor that indicates the magnitude impact of each independent variable. This is calculated as a regression parameter estimate divided by the Lenth's Pseudo-Standard Error, an estimate of the residual standard error. In discussions with Dell stakeholders, the Lenth t-ratio was communicated as the magnitude of impact factor.

Individual p-value and simultaneous p-value, as mentioned above, are parameters that identify the predictive power of each independent variable. The smaller the value the more predictive power, with 0.05 as the statistically significant threshold. Individual P-value represents the statistical significance for use as a predictor in a linear model and assumes all other constraints are inactive. This is likely satisfactory if there are few impactful criteria, but if there are several the individual p-value could over-predict significance. The simultaneous p-value adjusts for multiple comparisons and is more useful to determine significant predictors if several criteria are significant (SAS Institute Inc., 2015).

Figure 8 is a report table for the US configurable notebook business product line sorted by individual p-value for payment processing. Pay_Code_Lead_Time, at the top of the table, represents the lead time commitment from the payment team and should be highly correlated to the amount of time an order spends in the payment phase of the end-to-end process. This characteristic is based on other order criteria, and would not be a good candidate for predictive analysis. Most of the remaining criteria can be separated into two distinct buckets, payment type and customer type. Pay_Code and Payment_Terms describe the method of payment. Credit cards and gift cards should have much shorter cycle times than customer orders that require financing terms. Operational_Segment, Online_Offline_Flag, Parent_Channel, and Carrier_Code all are related to the class of customer purchasing the product. Larger customers that have done business with Dell in the past may have more streamlined financing processes compared to small businesses that order less frequently and need varying terms. For the payment methods chosen in this case study analysis, only Pay_Code was used to represent other payment description attributes.

Screening for Order_Process_Hours

Contrasts

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
Pay_Code_Lead_Time	3.18937	6.79	<.0001*	<.0001*
Operational_Segment	1.55449	3.31	0.0010*	0.5058
Pay_Code	-1.58780	-3.38	0.0008*	0.4314
Online_Offline_Flag	-1.35686	-2.89	0.0038*	0.9119
Payment_Terms	1.47368	3.14	0.0019*	0.7036
ShipTo_Country	1.25731	2.68	0.0073*	0.9857
Mfg_Lead_Time	1.27303	2.71	0.0058*	0.9793
Parent_Channel	-1.22279	-2.60	0.0091*	0.9945
Network_Hours	-1.19092	-2.53	0.0105*	0.9980
Carrier_Code	-0.97759	-2.08	0.0374*	1.0000
Facility_Hours	-0.88886	-1.89	0.0585	1.0000

Figure 8: Effects screening report for a 1000 order sample of payment processing data.

Screening reports were repeated 10 times for each process step with 10 different order samples. For each process step, the count of instances where order attribute p-values were less than 0.05 was collected in a single table. Attributes for the payment processing phase are listed in Table 1, limited to those attributes that occurred three or more times in the 10 screening runs. This table was then shared with members of the order experience program team and functional operational managers to determine if the anticipated business critical criteria aligned with the reporting results.

Significant Payment Processing Order Attributes	Count of screening p-values <= 0.05
Network_DayOfWeek	7
Network_HourOfDay	7
Payment_HourOfDay	7
Pay_Code_Lead_Time	4
Pay_Desc	4
Pay_Code	4
Payment_DayOfWeek	4
Channel_Desc	3
Facility_HourOfDay	3

Table 1: Count of instances, across screenings, of attributes that had a p-value of less than or equal to 0.05 for payment processing

Many of the aggregated results were intuitive, such as an order with a longer quoted payment lead time took longer to process. The Pay_Desc and Pay_Code both describe the payment type, and as mentioned earlier only the Pay_Code was used to represent payment description. Differing payment options impacting the payment processing time was also intuitive to the stakeholders, who expected more time for orders that were purchased without a credit card. As a result, Pay_Code was used as the representative for all three of the attributes highlighted in green.

Temporal attributes accounted for five out of the eight that occurred at least three times in the screening, highlighted in yellow. In discussions with stakeholders, temporal differences were also expected. These were likely due to the labor schedule and prioritization of some build to stock orders earlier in the day. Order volume during the time of day and day of week when payment staffing was lower was less than 5% of orders. Therefore, differentiating on these attributes was ignored for this study. While this study does screen for hour of day order attributes, these attributes are not included in the next chapter's process flow diagram construction because parsing data into hours, in addition to other criteria, would create order populations too small for this study's modeling framework approach.

Channel_desc differentiates an order by the industry and size of the purchaser. After further investigation into the customer type, the only payment option impacted was financing. Customer classes impacted by the differentiation did not have significant order volume. Therefore, this characteristic was also ignored for this study.

This type of screening was repeated for the facility planning, build, inbound logistics, and outbound logistics process steps. Below are tables highlighting the highest count attributes from screening analysis. Explanations for how the attributes interact with one another and which were chosen to be included in the process flow diagram construction are also briefly discussed for each of these process steps.

For facility planning, significant attributes fall into two buckets. The first, highlighted in yellow in Table 2, are temporal impacts such as day of week and time of day processes begin. Day of week temporal attributes for each process step are related to one another, as some sub processes have a short duration and do not change the day of week value for subsequent processes. Facility Day was chosen as the attribute to represent the temporal impacts for the facility planning process. The second bucket of attributes, highlighted in green, are related to the specific product selected. Products specification and customer type attributes are very correlated, as products are designed to meet the needs of specific customer segments. The product selected can also impact the services tied to the order, such as expedited delivery or consolidation facility services. Differentiating at the unique SKU level would result in sub populations too small to analyze in subsequent modeling framework steps. To represent the green bucket of attributes, this study differentiated on the product brand identifier only.

Significant Facility Planning Order Attributes	Count of screening p-values <= 0.05
Product_Hierarchy_Code	10
Product_Line_Desc	10
Is_Fga	7
Shuttle_Hours	7
Carrier_Code	7
Shuttle_Method_Code	5
Mfg_Lead_Time	5

Facility Day	4
Merge_Facility	4
Shuttle Day	4
Merge_Hours	4
Src_Channel	4
Sku_Class	4

Table 2: Count of instances, across screenings, of attributes that had a p-value of less than or equal to 0.05 for facility planning

The build process step, where the order is in production, revealed only temporal attributes in the statistical screening aggregation. To account for this in the process flow diagram, the attribute representing the beginning of the build process was included in the process flow diagram.

Significant Build Order Attributes	Count of screening p-values <= 0.05
Shuttle Day	10
Facility_Hours	7
Build Day	6

Table 3: Count of instances, across screenings, of attributes that had a p-value of less than or equal to 0.05 for the build process

Attributes impacting the inbound logistics process, illustrated in Table 4, are grouped into three buckets. Facility Hours and Logistics Day of Week are both temporal attributes. Logistics day of week was chosen to represent the temporal daily impact. Shuttle method code, which describes the different inbound logistics services offered by Dell's third party logistics provider, was also selected as significant. Delivery method code is related to the direct ship flag attribute that determines if an order can bypass Dell consolidation facilities and ship directly to the customer. Some delivery methods require unique shipping labels to be applied to the packaging at Dell consolidation facilities. The direct ship flag attribute takes into account the unique shipping label differentiation and captures other reasons why orders require consolidation services. The direct ship flag was selected to represent the order flow paths for the next chapter's diagram construction.

Significant Inbound Logistics Order Attributes	Count of screening p-values <= 0.05
Shuttle_Method_Code	10
Facility_Hours	6
Log Day	4
Deliver_method_code	4
Direct_Ship_Flag	4

Table 4: Count of instances, across screenings, of attributes that had a p-value of less than or equal to 0.05 for inbound logistics

The last process, outbound logistics, can also be represented by three buckets of attributes in Table 5. Day of week is very important for orders that receive ground shipping because, depending on the carrier, weekend delivery may not be an option. Logistics day of week, the day logistics processes begin, was selected to represent day of week attributes. Green attributes, when combined, describe all of the shipping options available in the supply chain. Both the direct ship flag and local ship code attributes were selected to differentiate orders. Blue attributes influence the amount of time it takes for a ground shipment to reach the customer. Dell uses a zip code to zip code logic matrix to create the freight lead time attribute based on the source and sink postal codes. For this study, freight lead time was used as a differentiating attribute to represent the zip code impact of ground deliveries. The blue attributes do not impact shipment methods like next day and second day that have fixed delivery commitments regardless of zip code.

Significant Outbound Logistics Order Attributes	Count of screening p-values <= 0.05
Log Day	10
Direct_Ship_Flag	7
Local_Ship_Code	6
Build Day	4
ShipTo_PostalCode	4
Freight_Lead_Time	3

Table 5: Count of instances, across screenings, of attributes that had a p-value of less than or equal to 0.05 for outbound logistics

Creating these analysis tables for the identified sub processes required both data analysis and stakeholder discussion to determine the significance of and relationships between order attributes. Confirming dependencies between attributes was a manual process, and can vary across regional products based on the underlying supply chain. This same set of attributes was re-examined for a flagship desktop product line pilot project. Differences and influencing factors for the desktop attributes will be discussed in chapter five.

The screening results were also powerful in revealing the lack of predictive power for certain criteria. System quantity and boxes shipped were two of the order characteristics that were thought to be significant drivers of cycle time variation. For some product lines this was confirmed in the data, but for others, system quantity had weak predicting power. Figure 9 shows these attributes in an effects screening report for configurable notebooks ordered in the US. Individual p_values for these are over the 0.05 threshold of statistical significance in all 10 screenings.

Term	Contrast	Lenth t-Ratio	Individual p-Value	Simultaneous p-Value
System_Quantity	0.73942	1.57	0.1188	1.0000
Boxes_Shipped	-0.06247	-0.13	0.8966	1.0000

Figure 9: Example payment processing screening output for system quantity and boxes shipped attributes

2.4 Statistical Validation of Independent Processes Cycle Times

Generally, configurable products that are manufactured after completion of the order process follow a first in first out (FIFO) methodology through the system. Processes will accept the order that has been waiting the longest in the queue. Stakeholders in the Order Experience Program and supply chain functions assumed that by using a FIFO system with ample capacity and no prioritization at each stage that there would be no correlation in cycle time performance between process steps. If a product takes an abnormally long time to pass through payment processing, it is not more likely to take longer in the subsequent process steps. If each process step is indeed independent, or has very a small correlation to other process steps, then it allows for the simple addition of individual process cycle times to get to a total order cycle time.

There are reasons why this independence assumption could potentially be flawed. There could be a prioritization scheme at some process steps that favors orders in the queue that might be tracking late to the committed delivery date range. If this type of scheme was in place, then processes early in the supply chain might show a negative correlation to subsequent processes. Take, for example, an order that initially was assigned ground shipping, which typically takes three to five business days, that finishes the manufacturing phase with only one day left in the delivery commitment. A prioritization scheme could upgrade this "tracking-late" order to next day shipping to make up for the previous process delays. Conversely, an order that completed the manufacturing phase with six days left in the delivery commitment could be downgraded to ground shipping to save the system money. While system capabilities allow for this type of prioritization, it is currently not used for build to order products.

Another potential violation of this assumption would be if queue wait times between processes made up the majority of the cycle times. If capacity at each process phase were less than incoming order volume, queues could form at each step that cause wait times to exceed process time. During high order volume periods, this could cause uniformly high cycle times across the supply chain. Order volume much below capacity limits would not cause long queue wait times. In an excess capacity scenario, cycle time would mostly be determined by the underlying process durations. Dell build to order products are made in a just-in-time fashion where capacity is high enough to handle significant order variability. Cycle time correlation between processes due to capacity constraints in the system are not expected.

To test the independence assumption, pairwise correlations of process cycle times were analyzed. Each process step's cycle time was compared to the cycle times of each other process step using the Pearson product-moment correlation coefficient. Coefficient values are calculated using the following equation where x and y are response variable values:

$$\rho = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2}\sqrt{\sum(y-\bar{y})^2}}$$

A correlation value of zero indicates no correlation and a correlation value of 1 or -1 indicates a strong positive or negative correlation (SAS Institute Inc., 2015). Table 10 shows the pairwise correlations for process cycle times.

Multivariate

Correlations

	Order_Process_Hours	Network_Hours	Facility_Hours	Build_Hours	Shuttle_Hours	Merge_Hours	Deliver_Hours
Order_Process_Hours	1.0000	-0.0156	0.0022	-0.0017	-0.0027	0.0114	-0.0059
Network_Hours	-0.0156	1.0000	0.0555	-0.0298	-0.0472	0.0371	0.0090
Facility_Hours	0.0022	0.0555	1.0000	-0.0275	-0.1245	0.0307	0.0140
Build_Hours	-0.0017	-0.0298	-0.0275	1.0000	-0.0098	-0.0312	0.0031
Shuttle_Hours	-0.0027	-0.0472	-0.1245	-0.0098	1.0000	0.0745	0.0072
Merge_Hours	0.0114	0.0371	0.0307	-0.0312	0.0745	1.0000	-0.0204
Deliver_Hours	-0.0059	0.0090	0.0140	0.0031	0.0072	-0.0204	1.0000

Figure 10: Multivariate correlation report that shows pairwise correlations for each process cycle time

As illustrated in the report above, there is very little correlation between the different process step cycle times. All of the coefficients are very close to zero. The most significant correlation is a negative relationship between shuttle, or inbound logistics, hours and facility planning hours. This suggests that orders that take longer in the facility stage will be slightly faster in inbound logistics compared to the rest of the population. Looking at the plotted data in Figure 11, this relationship is less pronounced for short shuttle cycle times and longer facility cycle times.

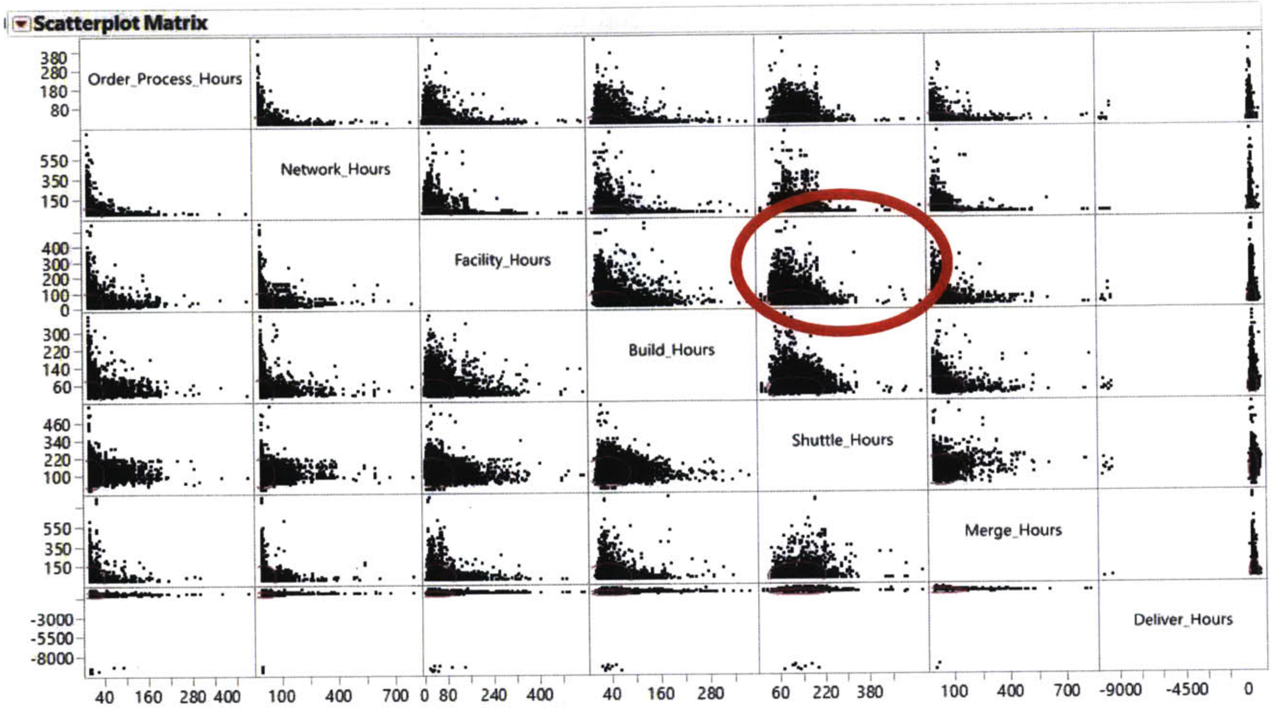


Figure 11: Scatterplot matrix illustrating the relationship of the cycle time data across process steps. The Facility Hours compared to the Shuttle Hours is circled to highlight the largest correlation relationship.

Because delivery date commitments are heavily influenced by long tail events, not accounting for this small negative correlation when adding process steps together could create a conservatively long end-to-end lead time forecast compared to the actual data. Validation of the modeling framework outputs in the next Chapter will examine the relationship of the simulation to historic order data.

3. Simulation Modeling Process

This chapter will discuss the methods used to construct a current state simulation model for the selected BTO business notebook product line. The first section discusses how to use the previously identified statistically significant order attributes to create process flow trees for each phase. The purpose of using process flow trees is to separate the orders into populations to account for attribute driven variability.

The second section reviews how to fit distributions to the separated order populations for each process step. Calculated distributions will be used to represent the process step in a simulation model. This section also discusses approaches used to address inconsistencies in the order dataset.

The third section discusses how the simulation model was constructed. The model combines the process flow trees from the first section and random sampling against the fitted distributions from the second section. The objective of the model is to simulate end-to-end cycle times for each branch of the process flow diagram.

The fourth section explores how Dell delivery commitment methodologies could be applied to the simulation model results. Simulated end-to-end cycle time distributions for each branch are leveraged to forecast delivery ranges. This section also calculates the proportion of orders that are predicted to be early, on-time, and late based on the delivery commitment.

The fifth, and final, section of this chapter investigates efforts to validate the simulation model. End-to-end distributions, delivery commitments, and on-time percent were shared with internal stakeholders and compared to the current state supply chain equivalents. This section also discusses methods used to address concerns in the validation process to better align the model to the current state.

3.1 Process Flow Diagram Construction

In the previous chapter, statistically significant order attributes were identified for each process step. A process flow diagram can be constructed using these attributes to represent potential order flow paths through the supply chain. Each branch is a series of process steps characterizing a unique order experience. Because payment and logistics phases are product independent, each supply chain phase, payment, manufacturing, and logistics has its own diagram. To determine the end-to-end supply chain paths, all possible combinations of the three phase diagram branches are created. For example, if there are two branches in payment, six branches in manufacturing, and three branches in logistics, then there would be a total of 36 (2*6*3) order flow paths once all combinations of the three are determined. These supply chain flow paths are later used to aggregate cycle times across processes to determine end-to-end order cycle times.

One caveat to this approach is that some order attributes can impact more than one process phase. The differentiation of an order that is directly shipped to a customer versus an order that requires a trip to a Dell consolidation facility is an attribute that affects both manufacturing and outbound logistics. Combinations of supply chain branches between manufacturing and outbound logistics must take this relationship into account, meaning no direct ship manufacturing branches can pair with a consolidation outbound logistics and vice versa.

For each supply chain phase, significant attributes from the statistical screening analysis were further examined to ensure accurate representation in the diagrams. Attributes vary in the detail they provide for an order. Some are simple true/false flags, providing a binary paring of options. Others contain many more options, such as hour of the day or number of systems in an order. Incorporating an attribute into the process diagram does not necessarily require each option to have its own branch.

For the payment phase, as mentioned previously, payment code was the only attribute selected as statistically significant and validated by stakeholders. Components of payment code considered for this study include financing terms, each credit card option, and gift cards. These components represent over 80% of the orders in the dataset. Other payment options were ignored to simplify the process diagram and modeling process. A modeling simplification was to bundle payment codes that had similar cycle time performance. The six credit and gift card options had very similar cycle time distributions, but financing typically had longer and more variable cycle times. Therefore, the process flow for the payment step was only split into two subsets of the population, credit/gift cards and other.

A similar approach was used for logistics, except more criteria were deemed significant through the screening process. Criteria utilized for this study were the direct ship vs Dell consolidation flag, shipping method, day of week shipment begins, and forecast freight lead time. Only shipping methods ground, next day, and second day were used in this study, representing over 90% of the order population. Freight lead time was selected as a proxy for length of ground delivery orders. Dell differentiated lead times based on the beginning and ending zip code of the orders. Using the predicted logistics lead time instead of zip codes helped to simplify the process flow diagram and modeling. Figure 12 is the logistics diagram. For each branch, cycle times are differentiated by the logistics day of week to account for carrier network weekly scheduled.

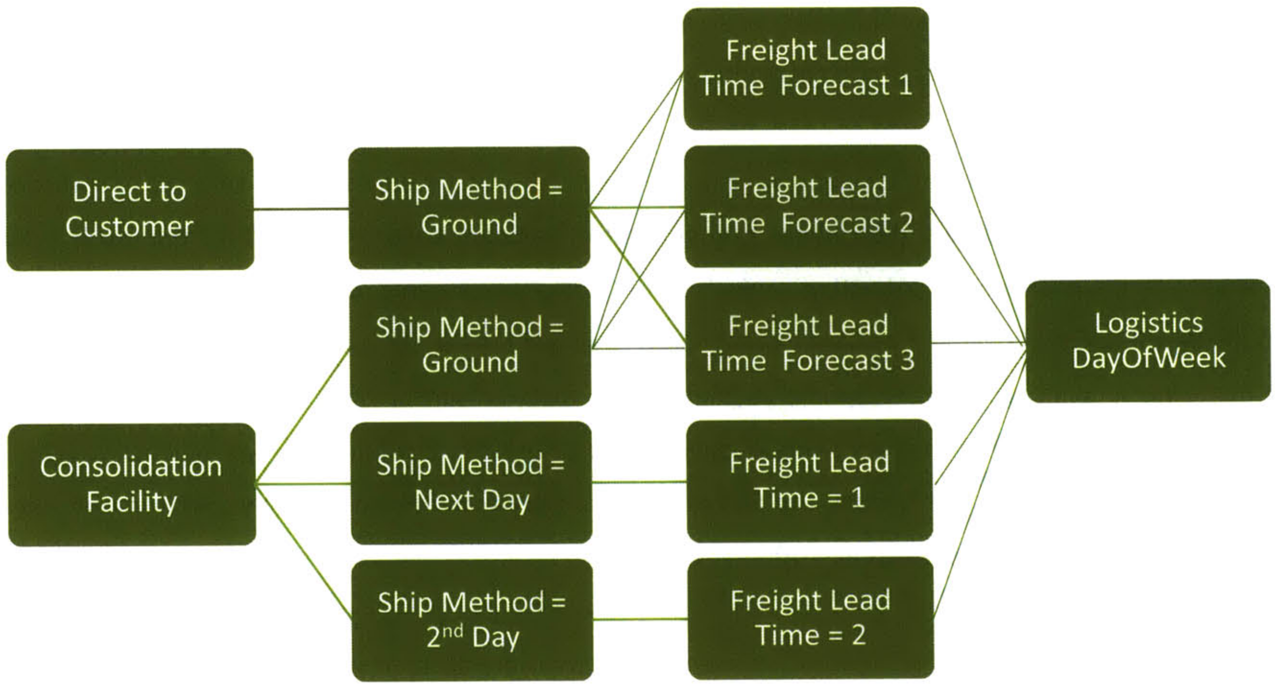


Figure 12: Outbound logistics process flow diagram

For the manufacturing phase, the branches span the remaining five process steps, network planning, facility planning, production, inbound logistics, and, if needed, consolidation. For process steps that have very short cycle times, such as network planning and consolidation, separating the order population based on statistical screening criteria does not add much value to the simulation model. These process steps represent a few hours in a two-week end-to-end order process. Longer and more variable process steps were more granularly represented in the diagrams. Key order criteria impacting the manufacturing processes were product, day of week each process step begins, direct ship vs consolidation, and inbound logistics method. Facility planning and Build processes have similar day of the week performance for weekdays compared to weekends. This allowed for grouping of these day of the week attributes into two buckets for each process, instead of seven to represent each day of the week individually. This simplified the flow diagram and simulation process.

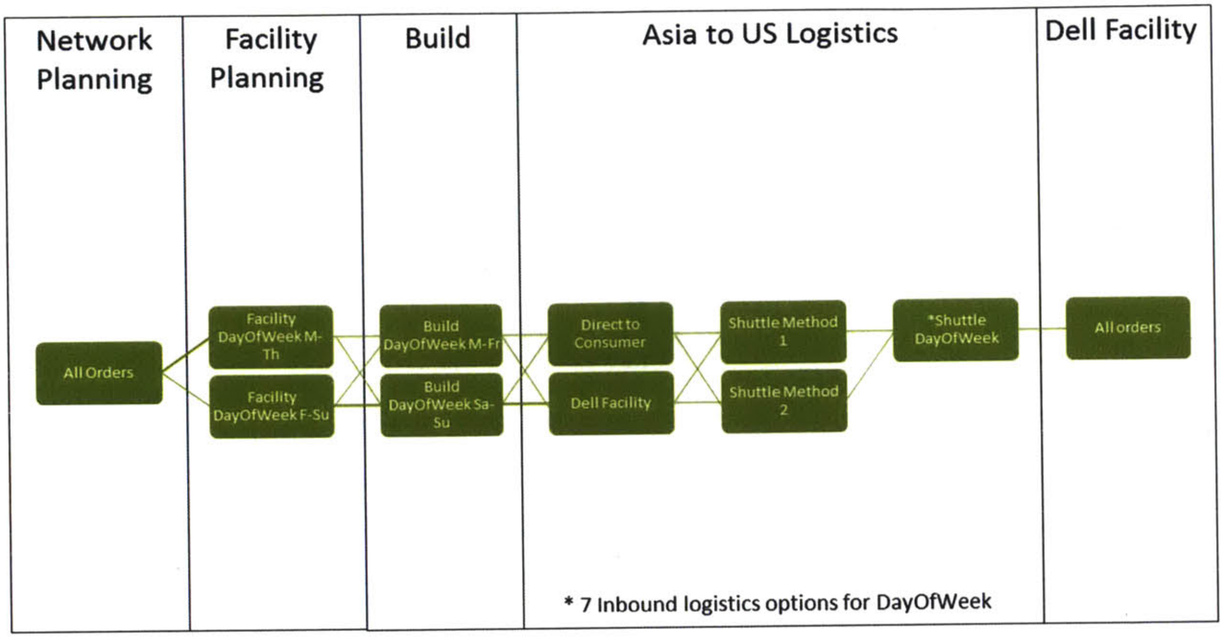


Figure 13: Manufacturing process flow diagram

3.2 Data Parsing and Fitting Distributions

The previous section created process diagrams to represent unique order flow paths. This diagram can be used to separate the order data based on significant order attributes into distinct populations. With the order data separated, the next step in the modeling framework is to fit distributions to the cycle time data for each process step branch. These distributions will represent the process steps in a simulation model.

In 2015, Kara Pydynkowski performed a similar study of a stock product line to determine the same day shipping eligibility. Her analysis relied on characteristics used in the current state lead time setting engine to differentiate the population. The approach used the @risk platform to test various fit options. Likelihood functions were generated to determine which fit should be used in the simulation. Distributions were then sampled and added together to achieve an end-to-end cycle time view that was then compared to varying delivery cutoff times to determine same day shipping eligibility (Pydynkowski, 2015).

This study uses a similar approach to derive the appropriate distribution criteria that will represent each of the process step options. First, a plot of each subset of data is generated for visual inspection. Figure 14 illustrates a plot for the inbound logistics process. Plotting the data helps to identify any potential data issues or unique characteristics of the underlying data. Any issues identified in this step must be addressed to ensure final modeling results are actionable.

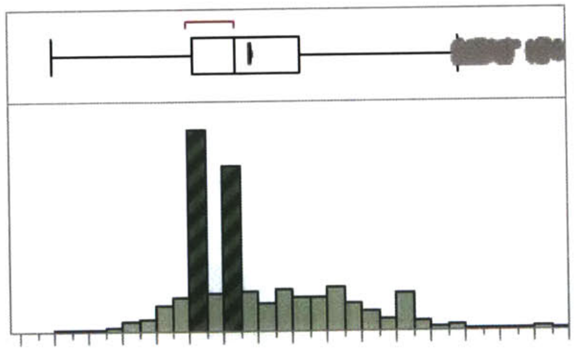


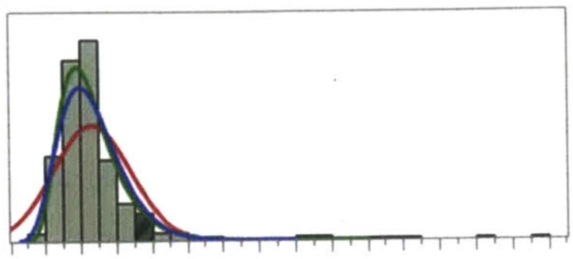
Figure 14: Histogram of one branch of inbound logistics cycle times illustrating lumpy data

For the example above, when plotting data for inbound logistics orders that were directly shipped to customers, a distinct lumpy pattern was identified where a more normal or lognormal distribution was expected. This observation was discussed with members of the order experience program and logistics teams to identify the root cause of the lumpy cycle times, as it would be challenging to fit a distribution to the data shape. The lumpy data was a result of a missing package scan in the dataset during the handoff from one logistics carrier to another. In anticipation of this potential scan issue, Dell had instituted a backstop value to be used in the event of a missed scan. This backstop value was an hour count based on the anticipated number of business days for inbound logistics. Time stamps that denoted the beginning of inbound logistics and final delivery were still valid for these orders, so as a fix for the data issue, inbound and outbound logistics processes were combined into one cycle time so a fit could be calculated and used in a simulation model.

After inspecting the subsets of data for inconsistencies, the next step is to determine the appropriate distributions to use for building a simulation model. This study examined normal, lognormal, and Gaussian distributions for potential fit to the data for each of the 84 process branch nodes. A likelihood measure for each distribution was then compared to determine which distribution provided the best fit. Likelihood measures uncertainty in the fit model with a likelihood-ratio test. The parameter is created by taking the difference of the likelihood of the fitted model, a fitted distribution in this case, and the likelihood of a predictor less reduced model, a linear fit using only an intercept parameter (SAS Institute Inc., 2015).

In every instance, the lognormal distribution provided a better fit than the other alternatives. This makes sense as, in general, as cycle time populations are constrained by zero and have medians below averages because of a long cycle time tail distributions. The mean and standard deviation are the outputs of this fitting process, and are used in the simulation modeling.

Figure 15 illustrates the process for determining distributions fit. Likelihood measures for fitted distributions below are listed in the legend. Lognormal had the lowest value, and therefor best fit across the three options. Lognormal fit was consistently the best across many of the order population cycle times.



Normal – Likelihood 32,595

LogNormal – Likelihood 29,651

Gamma – Likelihood 30,259

Figure 15: Histogram and fitted distribution likelihood values for the build process

3.3 Simulation Model Construction

The previous two sections of this chapter created a process flow diagram and calculated distribution branch parameters for each process step. The next step in the modeling framework is to randomly sample against each of the process cycle time distributions several times. These samplings will be summed across the process flow diagram branch paths to predict end-to-end cycle times for each supply chain offering. This approach will provide a unique end-to-end cycle time distribution for each possible combination of significant order attributes represented in the process diagrams. Simulated end-to-end cycle times from this model will represent the business as usual current state supply chain and will be used for further analysis in later sections of this thesis.

Excel was used to randomly sample against the fitted distributions. One thousand instances were generated with replacement using the fitted distribution parameters for each process step node on the process flow diagram. Each of the thousand instances in the simulation represents a potential order and has a corresponding cycle time sampled from each of the process step distributions. The next step is to add up the process steps to represent a complete end-to-end diagram branch. For branch elements that do not depend on the time of day or day of week, the cycle time components from each row are added together to correspond to the diagram layout. Because we previously tested the assumption of independent cycle times across process steps, cycle times can be simply added together to calculate the end-to-end cycle time.

For diagram branch elements that do depend on the time of day and day of week, temporal logic must be added to the simulation to identify the appropriate distribution to use given the simulated start time of day and day of week. The facility planning, production, inbound logistics, and outbound logistics phases have different distributions based on the day of week the process begins. Random sampling of historic start hour-of-day and day-of-week data was used to represent when, during the course of a week, an order would enter the system. Creating a start time of day and day to be paired with end-to-end cycle times is important to determine on-time performance when considering temporal attributes. Day of week and calendar vs business day conversions also impact both the commitment and the cycle time distributions. Cycle times of processes are then added in sequential order to determine the day of week each process begins for each simulated order. Logic operations in the model then chooses the appropriate day of week distribution to include in the end-to-end cycle time.

The output of the simulation is an end-to-end cycle time for each potential order flow path, as determined by the significant order attributes in the process diagram. The expectation is that this simulation will represent the cycle time performance of the current state supply chain offerings. One benefit of this study's approach is that it accounts for order attributes that may not be utilized by Dell when committing a delivery range to the customer.

One such characteristic is the flag that indicated if an order was directly shipped to a customer or if it required a trip to a Dell consolidation facility. In Dell's current processes, all of these orders are aggregated into one flow path and provided a single delivery date range commitment. The simulation from this study provides two flow paths based on this attribute, allowing for more detailed and accurate delivery date range commitment. Figure 16 illustrates how differentiating on this attribute can impact the higher cycle time end of the distribution ranges, 95th percentile chosen for this example. The last day in a delivery date range is calculated based on this end of the distribution, potentially providing Dell opportunities to commit smarter lead times to customers.

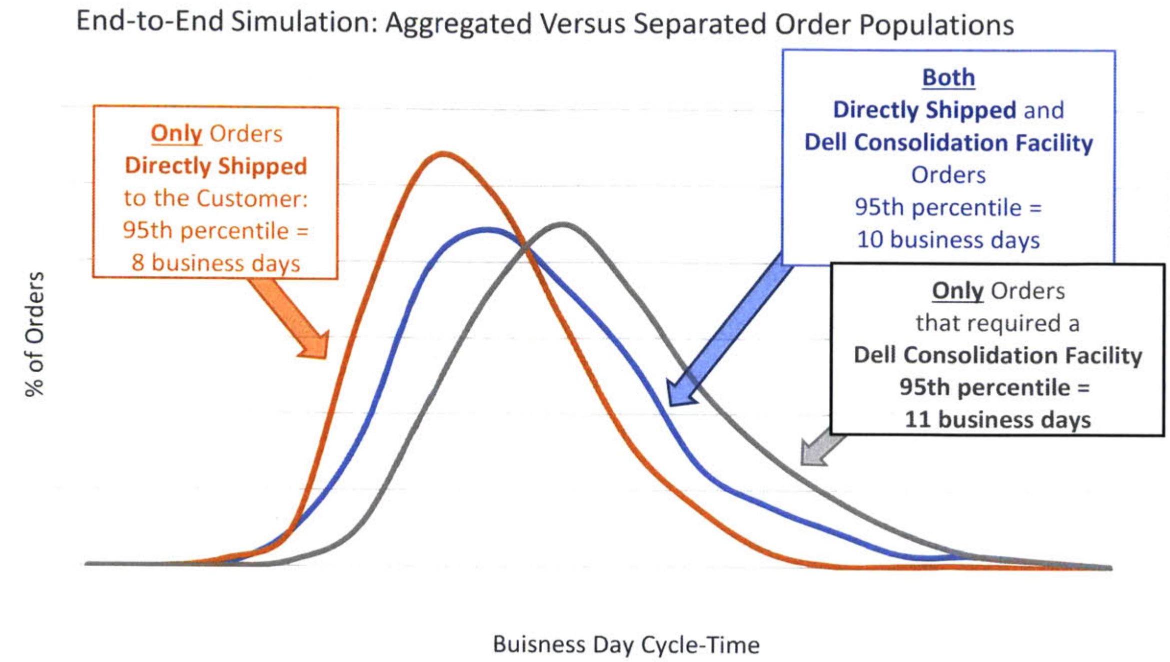


Figure 16: Cycle time distributions for one aggregated order population compared to the distributions differentiating on the attribute that identifies an orders eligibility to be directly shipped to the customer.

This example and other opportunities for Dell to provide more detailed delivery date range will be further examined in the next chapter.

Another benefit to this study's modeling approach is that simulation occurs at the sub-process level. The outputs of the modeling are the end-to-end cycle time distributions of unique flow paths. However, retaining insight into the sub-process cycle time distributions can reveal which processes contribute most to the end-to-end cycle time variability. Also, because the process steps are assumed independent, distributions for individual process steps can be altered and re-inserted into the model. This can be useful for assessing possible process improvement or other changes in underlying processes. Uses of these types of changes will be further discussed in the next chapter.

Subsequent sections of this chapter will translate the modeling outputs to current state business metrics and validate the modeling cycle time distribution outputs. End-to-end cycle time distributions will be used to calculate expected delivery date ranges and on-time order performance for each supply chain offering. Forecast delivery commitments and on-time performance will be used in the validation process.

3.4 Translating Simulation to Business Performance

Dell has a commitment process that generates lead times for products based on certain attributes known at order entry. These include length of time it takes the payment to clear, availability of items in the order, delivery method, shipping provider, factory location, delivery address, and holiday periods (Shipping and Delivery, n.d.). To calculate the expected delivery date (EDD), the last date a customer can receive an order without being late, attribute specific lead time forecasts from the payment, manufacturing, and logistics are added together. Individual phase lead times are created to maintain a certain small threshold of late orders in each phase. The level of acceptable late orders can be altered to provide a more or less competitive commitment to the customer but typically is limited to between 0 and 10%.

One key difference between the current commitment process and the simulation model is that the model calculates the EDD based on the end-to-end distribution, not a summation of phase lead times. Because these processes have little correlation, orders that are late in one phase are unlikely to be late in the other phases. Combining individual phase lead times that allocate for a specific threshold of orders that exceed a late threshold at each phase creates an unnecessary buffer. Taking an end-to-end view while maintaining insight to the individual process steps was one of the key considerations in developing this modeling framework. For this study, an end-to-end late threshold of 5-10% was used to calculate the EDD.

A simple example was used to communicate the value of an end-to-end view to capture the variance pooling across the process steps due to their independence. Assume each phase is normal with a mean of 0 units and standard deviation of 1 unit and has no correlation. The individual lead times, allowing for a 10% late threshold, would be approximately 1.3 units for each phase. Aggregating all three lead times would yield a 3.9-unit lead time commitment. The end-to-end process would have a mean normal parameter equal to the sum of the individual means, 0 units. The end-to-end standard deviation would be equal to the square root of the sum of squared standard deviations from each process step. This would be equal to the square root of three in this example. Allowing for the same 10% threshold of late orders, the lead time commitment would be about 2.3 units. By taking an end-to-end view, the lead time is more accurate and is reduced by over 40%. In reality process steps have varying distribution parameters, but the concept remains true and helped to get buy-in for the end-to-end simulation model results.

Simulated orders can be categorized as on-time, late, or early by pairing a delivery date range to the end-to-end cycle time distribution. Once an end-to-end EDD is calculated, this study uses the same method as Dell to determine the delivery date range. Summarizing this method from the introduction chapter, Dell uses a competitive framework to identify the delivery range used in the lead time commitment. In general, as the EDD gets further out, the delivery range gets wider. These ranges are benchmarked to industry peers and adjusted to align to Dell's supply chain. To calculate the beginning of the committed delivery date range, the competitive range is subtracted from the EDD. Orders that fall within the beginning date and the EDD are considered on-time. Order delivered before the range are early and after are late.

The simulation model, paired with the calculated delivery date range provides early, on-time, and late percentages for each order branch. These results can be aggregated to a single on-time performance view representing all possible product flow paths weighting the percentages with the historic order volume of each branch. Dell stakeholder track on time performance at the product line level. A modeling output, like product level on-time performance, that aligns to existing reporting metrics is useful for presenting results throughout supply chain stakeholders. Validation efforts, comparing the simulation to the current state, are also important for discussing simulation results with stakeholders.

3.5 Validating Simulation to Data

It is important to determine how well the simulation model represents the current state supply chain before developing recommendations based on the simulation analysis. The intended uses of this model are to find opportunities to improve customer delivery commitments and provide cycle time targets to supply chain process steps. Therefore, it is important to validate the simulation results to historic end-to-end cycle time data, with emphasis on the long tail distribution where EDD values are determined. It is also important to get Dell stakeholders to confirm that simulation outputs are reasonable given their supply chain expertise.

It is important to note that Dell's process for determining an EDD for a product is not a rigid process. Because a threshold range for late orders is used as the determinant, there is some flexibility in the commitment. Communicating a shorter lead time within the threshold range can make an offering more competitive and appealing to the customer. Conversely, if a longer commitment if communicated, it is more likely that the order will not arrive late to the customer. Because of this, delivery commitments for historic orders were not used in the validation process. Instead, end-to-end cycle times for historic orders with the same attributes were compared to the simulation forecast cycle times.

Average and 95th percentile values of end-to-end distributions were calculated for branches of the product flow diagrams to compare the simulation and historic data. Comparison of these metrics would indicate how well the critical segments of the distribution matched. The 95th percentile is representative of the point on a distribution where an EDD could be located for a given branch. Because the end-to-end distribution shape is a bell curve, the average value of the distribution indicates the cycle time of a significant portion of the order volume. Validating lower percentile values was less valuable for this study because the delivery date commitment process does not use this end of the distribution for decision making.

Table 6 shows the average and 95th percentile for both the simulation and the actual historic end-to-end distributions for the month of August 2016. Attributes for historic orders were aligned to those of the simulated process flow diagram branches. Branch attributes are hidden to protect proprietary information, but are given a unique identifier for reference. The table shows the comparison for seven examples chosen at random from the larger branch dataset. For this comparison, only categorical attributes, like payment type, inbound logistics method, direct ship flag, delivery type, and freight lead time were used to differentiate orders. Temporally differentiated branches were aggregated at each process step to simplify the comparison to the historic data. Temporal attributes were still used in the simulation to determine the correct cycle time distribution at each process step to sample based on the simulated start time of day and day of week.

	Branch ID (hidden attributes)						
	1	2	3	4	5	6	7
Simulation μ	5.8	7.6	6.3	6.7	5.5	7.6	6.3
Actual μ	5.9	8.0	6.4	6.7	5.5	7.3	6.4
Actual μ - Simulation μ	**0.2**	**0.4**	**0.0**	**0.0**	**0.0**	**-0.2**	**0.1**
Simulation P95	8	11	9	10	9	11	9
Actual P95	8	11	9	10	9	10	9
Actual P95 - Simulation P95	**0**	**0**	**0**	**0**	**0**	**-1**	**0**

Table 6: Average and 95th percentile values from simulation and historic order cycle time distributions.

In each of the example branches, the simulation was very close to the historic order cycle time performance. Cycle time differences between historic data and simulation ranged from -0.2 and 0.4 business days, with a 5% maximum deviation of any one branch. For three of the branches, average cycle time aligned to the tenth of a business day. A 5% deviation from average performance was acceptable to stakeholders to represent the current state cycle time performance, and all branches were within this tolerance.

95th percentiles of the distributions were also compared. These values are integers, because the percentile value chosen is a multiple of 1/(n-1), where n is the number of observances in the dataset. The maximum deviation from the historic data was one day, and only occurred for one of the example branches. A difference of one business day could represent up to 24 hours in underlying distribution differences. Because of this, internal stakeholders wanted very close alignment for the 95th percentile integer comparison. A difference of one day was acceptable for Dell stakeholders to represent the tail distribution of the orders. No branches exceeded one-day difference for the 95th percentile.

Dell stakeholders also wanted to see a comparison of the percent of orders that would be on-time for the historic order population and the simulation. For both populations, this study used the method described in section 3.4 to calculate the EDD, allowing for a 5% late threshold. The Dell competitive range framework was then referenced to determine the appropriate delivery range to combine with the EDD of each branch. For the same seven branches as the previous validation table, Table 7 shows the on-time calculation for the historic data set and the simulation. In both historic and simulated calculations, late orders were up to 5% based on the calculation methodology of the EDD. On-time percentage differences ranged from -4% to 15% across the branches, with a total volume weighted on-time difference of 6%. Comparing the distribution and on-time validations, branch 2 had the largest mean difference and orders tended to be slightly earlier in the distribution compared to the historic data, resulting in the 15% on-time difference. The 6% aggregate on-time difference was acceptable to the Dell stakeholders. However, because on-time results varied within the branches, they wanted to retain visibility into the individual branch on-time values when discussing recommendations based on the simulation results

	Branch ID (hidden attributes)						
	1	2	3	4	5	6	7
Historic data on-time %	53%	60%	39%	43%	12%	69%	37%
Simulation on-time %	49%	45%	34%	38%	16%	61%	34%
Historic - Simulation %	**4%**	**15%**	**5%**	**5%**	**-4%**	**8%**	**3%**

Table 7: On-time accuracy for historic data and simulation results using the same Dell delivery date range commitment method.

4. Improvement Opportunities

Constructing a simulation model that aggregates cycle times for each process step provides flexibility for identifying opportunities for business improvement. Each process can be altered and examined to explore the impact to the end-to-end performance. Processes can even be swapped out for hypothetic distributions of new supply chain flow paths. Also, unique end-to-end supply chain options, based on statistically significant order characteristics, are separated from the broader population to allow for smarter EDD generation. These sensitivities to the modeling and lead time calculations were leveraged to find ways to improve on-time performance of each case study regional product selected. A combination of these were used to create a potential future state of operations that achieves Dell's on-time performance goal.

4.1 Smarter Lead Time Commitments

Dell uses several criteria to determine an EDD for each order. Only order characteristics known at the time of order entry can be used to set the EDD. For the current state, these include product, payment type, delivery method, customer location, shipping method, component inventory, and additional services required. The statistical screening and process flow diagram construction stages of the modeling framework identify key characteristics that drive cycle time variation. Attributes used in current state lead time calculations were identified as significant, but other characteristics were also highlighted as important differentiators.

The two biggest opportunities for smarter lead time setting were differentiating the order population by inbound shuttle method and direct ship vs consolidation. Dell's supply chain has multiple methods for transporting products from the ODM to the final delivery country. Each method has a different quoted service level and cycle time performance. The inbound logistics method varies by customer class, seasonal cycle, and product type, but orders have committed lead times based on a mixed population of logistics services. For orders where the vast majority of the population uses one service, this differentiation will show little on-time improvement. However, high volume US business products had a more even split between at least two inbound logistics methods. For the mixed populations, if the transportation option is known at time or order entry, and delivery range held constant, on-time performance for US orders can show on-time improvements of 15-30%.

The other order characteristic underutilized in EDD commitment creation was directly shipping to the customer. Dell orders can require routing to a consolidation facility for additional services or be routed directly to the consumer. Simulation identified a 10-15% improvement when differentiating on the direct ship outcome, varying based on the percentage of the order population that qualify for the direct shipping option. Also, for the direct to customer shipping option, a more competitive lead time was allocated to the qualifying population. Unfortunately, this is a characteristic that is determined by systems that execute after the order entry process in the current state. Upfront knowledge of direct ship qualification would allow for population separation and more accurate lead time commitments.

4.2 Process Distribution Improvement

Another method for on-time improvement is altering the underlying process step distributions in the model to simulate process improvement or inclusion of a new supply chain offering. It is important to consider the feasible limits of existing processes and the financial constraints for process improvement or switching to new systems. Another consideration when reducing cycle time tail distributions is that as the processes improve, the EDD commitment and delivery range will also reduce. This phenomenon provides a more competitive offering to the customer, but can limit the amount of on-time performance gain.

The first attempt to achieve Dell's future state on-time goal in the model is to uniformly reduce the standard deviation of each process step by a fixed percentage. The EDD for each product offering is still calculated by maintaining a designated threshold of late orders and the delivery range is follows the same competitive range logic framework. The first attempt also assumed smart lead time improvements from the previous section, differentiating on inbound logistics and direct to customer criteria. Figure 17 illustrates an example standard deviation reduction of 50% for two of the longer duration cycle time process steps, Facility Planning and ODM Production.

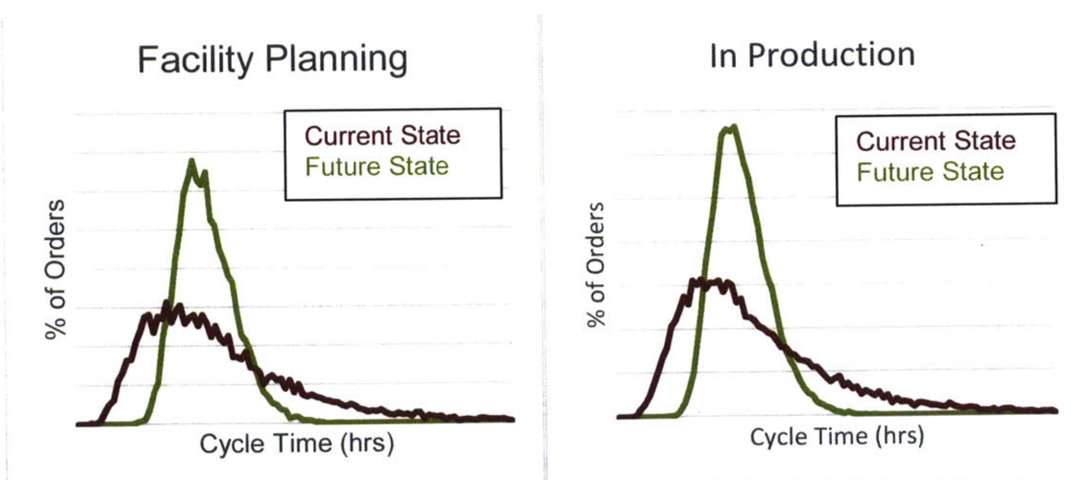


Figure 17: Example of the impact of process improvement through standard deviation reduction on cycle time distributions for facility planning and production processes.

Reducing the standard deviation has a significant impact on the longer duration tail of the distribution, but had very little impact on the mean. The flexibility of the simulation model allows for changes to the mean of the process step distributions, but mean changes were not used for the modeling outputs communicated to Dell stakeholders. Because delivery date ranges are committed based on the long tail of the distribution, mean shifts to the right would cause more orders to be on-time to the delivery window. This could be accomplished by holding orders that are forecast to be early to the delivery window during a process near the end of the supply chain. Alternatively, mean reductions would likely cause more orders to be early to the delivery range.

Once the final standard deviation reduction percent was determined, distribution metrics were created to socialize the results with the order experience program and functional leaders to determine feasibility and cost of implementing the model distribution improvements. Functional team metrics are typically communicated as the cycle time at specific percentiles and the average of the order population. These percentile and average values were created for each of the process steps, broken out by each of the significant order characteristics from the statistical screening. Also critical to acceptance of the metrics was communicating the end-to-end view along with the individual process metrics.

Dell has varying levels of control at each process step in the supply chain. While Dell has control over which delivery methods to use, Dell does not have as much control over improvements to the existing third party logistics provider offerings. Also, certain processes have experienced great improvement in the recent past, limiting the improvement potential from current state. Using feedback from the functional team leadership, improvement targets were re-aligned in an iterative process until all stakeholders were comfortable with the future state improvement targets. Processes that already realized significant improvements and processes where Dell has less direct control were allocated a 10% standard deviation reduction targets. These processes included payment processing, outbound logistics, network planning. The remaining process steps, facility planning, build, inbound logistics, and Dell consolidation, were allocated improvement targets of 20%.

In addition to reducing variation in existing processes, the model can simulate against hypothetical distributions of new supply chain offerings. One such offering simulated for US notebooks was a new one-carrier logistics offering combining inbound and outbound logistics services. This type of service would eliminate a handoff between carriers and utilize the more robust third party logistics network. Switching to this new service was expected to provide a more competitive commitment with higher on-time performance for little extra cost. Cycle time distributions were created to represent this service based on carrier information and manufacturer to delivery cutoff time assumptions. New efficient supply chain offerings did not include standard deviation reduction targets for the future state.

Figure 18 highlights the end-to-end distribution difference between a current state premium supply chain offering compared to the new combined logistics offering. The new offering has a tighter cycle time performance and the tail distribution is much thinner. On-time performance increased 20-25% using this new offering compared to the existing premium offering. With quantitative support from the modeling framework, Dell increased efforts to develop an implementation strategy for this offering.

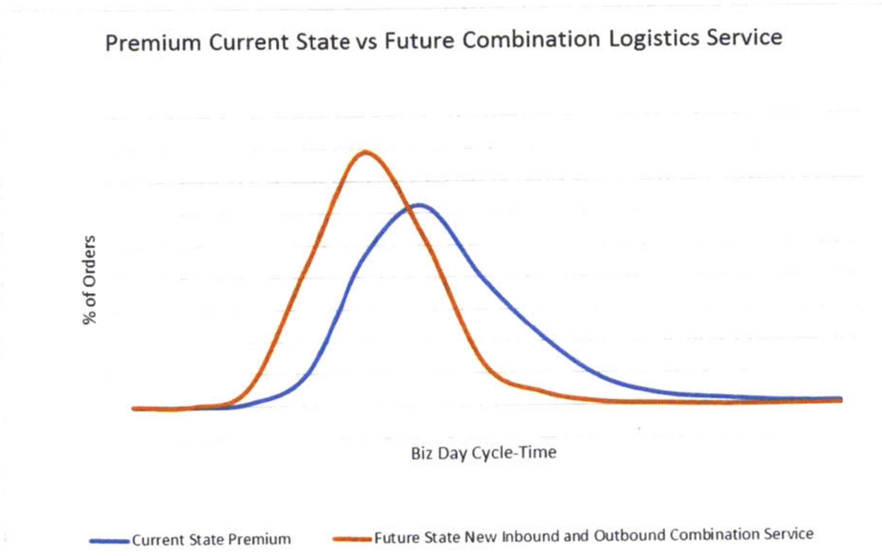


Figure 18: End-to-end cycle time distributions of current state premium offerings and future state options

5. Pilot Project: Smart Lead Time Generation for Direct Ship

One takeaway from using the modeling framework across multiple case studies was the impact of differentiating the order population based on direct ship eligibility. Orders that qualify typically have shorter cycle time performance and less variability than those that required additional services at a Dell consolidation facility. Implementing lead time changes for a sample product line was a feasible pilot project that could be completed and reviewed during the study timeline.

5.1 Case Selection and Data Availability

To determine an appropriate regional product line to analyze for the pilot project required collaboration with data specialists within the order experience program organization. An ideal order population for the pilot project would have a significant volume of orders that qualify for direct shipping. Also, this same order population would ideally have fewer factors driving consolidation facility work to simplify the study. After investigation and discussion with the order experience program, IT, and consolidation team leaders, a US desktop product line manufactured in Mexico was identified as a candidate meeting the above criteria. Over 80% of this product line qualified as direct ship eligible. ODMs used in Mexico can perform more services in house compared to those in Asia, simplifying the characteristics requiring consolidation processes.

In order for Dell to use an attribute to set a lead time, current state IT systems must contain the attribute at customer check out. The statistically significant attribute that indicates if an order is eligible to be directly shipped to the customer was determined after customer check out. To create this attribute prior to check out, this study identified reasons why an order would require consolidation services. Additional data sources such as attached software, palletizing, and more detailed logistics carrier lead time commitments provided better insight into characteristics that were known at order entry. These other sources required mapping to the original database prior to analysis. A new attribute was created utilizing these new data sources and it properly identified over 95% of the orders that required an order to flow through a Dell consolidation facility.

5.2 Modeling Framework Pilot Implementation

With the product line identified and additional data appended to the order information, the modeling framework was used to analyze the population. Statistical screening and collaboration with functional team leadership identified the key drivers of cycle time variability and were used to create a diagram representing the majority of supply chain flow paths, as seen in Figure 19. As with initial modeling efforts, only a subset of the ship codes, payment codes, and manufacturing lead times representing over 80% of the orders were utilized in the study to simplify the modeling process.

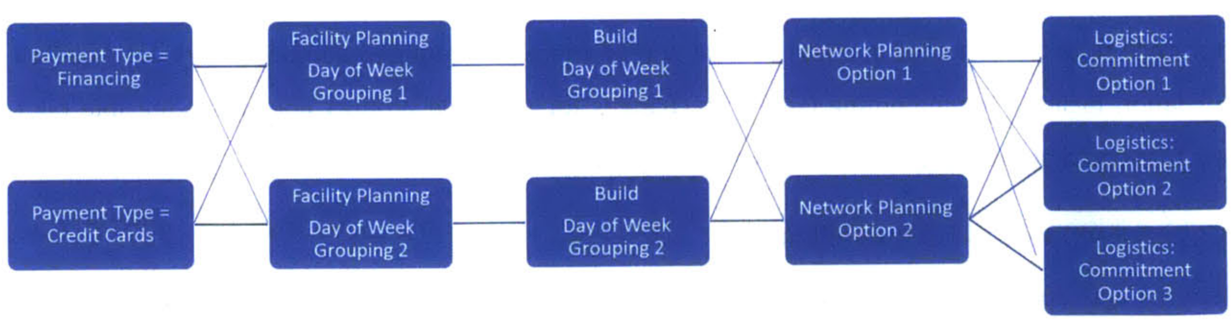


Figure 19: Pilot process flow diagram for desktop orders manufactured in Mexico

Statistical screening also helped to identify order criteria shared by the order population that requires consolidation facility services. Some of the reasons for consolidation included certain ship codes, attached software and hardware, and large order processing. The consolidation facility criteria were investigated individually to identify cycle time duration and lead time implications.

End-to-end cycle time distributions for each of the 24 branches of the decision tree were analyzed for the direct shipped population to determine appropriate lead time commitments. As an additional consideration, order entry day of week was also analyzed for the direct shipping population, as cycle time performance varies based on facility calendars and logistics carrier scheduled. Table 8 highlights the difference between the current state EDD calculation and the simulation forecast EDD based on a 10% late threshold.

Difference Between Current State EDD and Calculated Simulation EDD Allowing for 10% Late Orders

	Order Begin: Day of Week						
Logistics LT	**Sunday**	**Monday**	**Tuesday**	**Wednesday**	**Thursday**	**Friday**	**Saturday**
Option 1	1	-1	-1	-1	-2	0	0
Option 2	1	-1	-2	-2	-3	0	0
Option 3	0	-4	-3	-3	-3	-1	-1

Table 8: Pilot comparison of current state and simulation EDD values for three different logistics lead time options.

The simulation revealed that weekday orders that qualify for direct shipping had lead times that were up to two business days longer than needed. All branches of the process flow that were directly shipped to the customer had similar weekday results. Weekend orders took longer due to factory and logistics schedules, and the current state lead times were representative of the tail distribution of this population. The weekly shape of order cycle times was validated against a broader historic order population by the order experience data analytics team. Simulation results also revealed an opportunity to improve the lead time commitment for varying logistics options, but was not investigated for this analysis.

Orders requiring consolidation services had varying end-to-end distributions based on the specific service required. Visibility into each unique service was limited in the modeling framework dataset. Unique buffers were collaboratively quantified by the operational teams and added to delivery commitments. These services can be identified through a combination of order characteristics, including SKU, tied product information, and shipping method. Each of these characteristics are IT enabled for lead time differentiation in the current state.

5.3 Recommended Changes

Comparing the simulation results with the current state lead times revealed a mismatch in commitments. Implementing a two business day reduction in lead time commitments for weekday orders directly shipped to customers, in-line with model forecasts, should yield a 30-40% increase in on-time performance. This lead time reduction should be paired with consolidation service lead time adders to commit smarter lead times to customers.

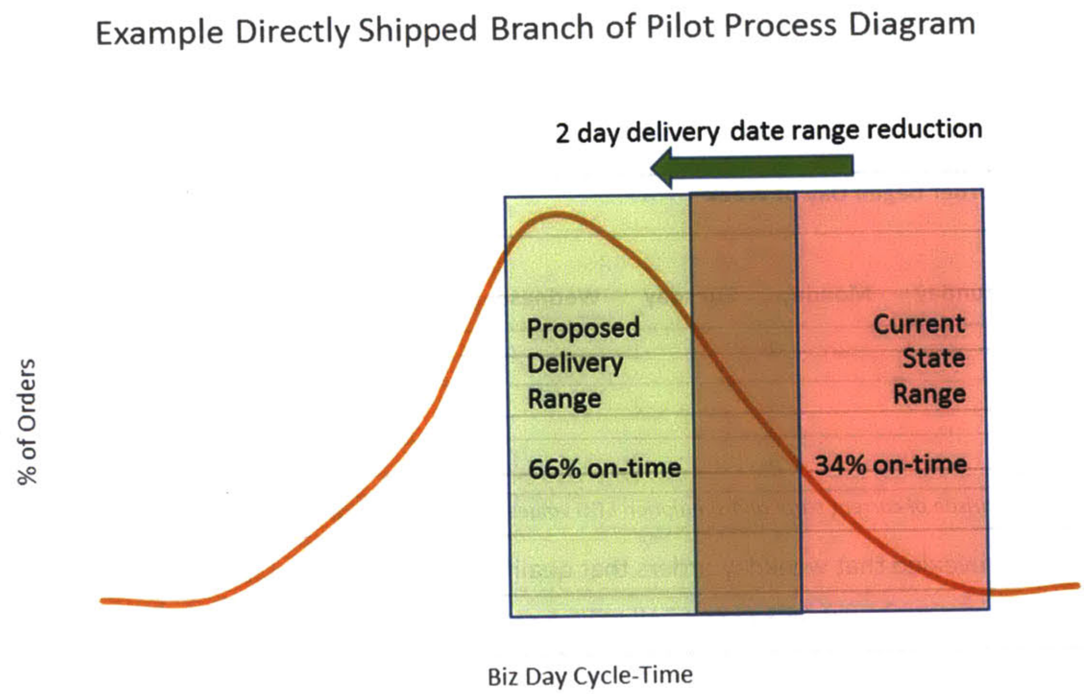


Figure 20: Illustration of the pilot two business-day commitment reduction with on-time percentage impact

5.4 Results

The US desktop product line adopted this lead time recommendation for two weeks in the fall of 2016, impacting just over 8,000 orders. Examination of the pilot population required waiting for final delivery results. For the two-week pilot, this total product line saw an increase in on-time performance of 39%. This also caused an increase in late orders by 8% and reduction in early orders by 47%. Included in the 8% late increase are orders that had missing delivery information and was calculated based on the final delivery, not first delivery attempt typically used to calculate on-time performance. While the 8% increase in late orders was acceptable by internal pilot criteria, this was a conservatively calculated value that was likely much lower, with more orders becoming on-time and early.

One day during the pilot was negatively impacted by an unaccounted for holiday in Mexico, Revolution Day Memorial. This day saw late orders spike to almost 20% with the more aggressive two business day commitment reduction. Orders spanning this holiday ideally would have added one additional day to the EDD calculated to account for the factory closure. This highlights the importance of pro-actively adapting to factory and delivery schedules, not simply relying on a historic dataset to calculate lead times.

With the success of this pilot, Dell planned to complete analysis and implementation for other US desktop product lines by the end of the first quarter of 2016. The pilot for this study took a team of four people approximately two weeks' worth of time to complete preliminary analysis of data, examine current state IT systems capabilities, and communicate delivery commitment changes to stakeholders. Repeating this analysis for other desktop product lines would likely take less time due to similar IT systems and stakeholders. The limiting factor in repeating this analysis is re-creating the direct ship attribute. Asia manufactured notebooks have more detailed consolidation facility service requirements that make re-creation of the attribute more challenging. However once the necessary order data are identified for the consolidation facility services, this pilot's process can be used to commit smarter and more accurate lead times to customers.

6. Conclusion and Future Work

6.1 Recommendations and Impact to Dell

The main takeaway across multiple regional case studies is that Dell needs to find a balance between being on-time and providing a competitive delivery commitment. Improving on-time delivery will require smarter lead time commitments and a reduction in variability at the individual process level. Both of these improvements will require investment in physical and IT process capabilities. Another alternative to investment is to commit a wider delivery window to increase on-time delivery. Weighing investment costs and delivery competitiveness will be critical to deciding the future of the order experience program.

The modeling framework identifies statistically significant order characteristics that Dell can leverage to commit smarter lead times to customers. Separating orders by criteria that drives cycle time variability provides a more accurate representation of order populations. Ensuring that these characteristics are known prior to order entry is critical to altering the current state lead time commitment engine. The lead time pilot project differentiated on direct ship eligibility and day of week, but there are other opportunities for more granular population separation.

In addition to smarter lead times, Dell can invest in improving or replacing components of the order experience supply chain. The modeling framework allows for an exploration of the impact of these changes on end-to-end cycle times and on-time performance. In general, handoffs between process steps were consistently identified as the greatest area of improvement. Assigning improvement targets needs to account for where cycle times materialize in the data and provide proper accountability to ensure cooperation across the handoff. It is important to note which supply chain components are common when aggregating results over multiple regional case studies, especially when assigning cycle time distribution targets. Also, assumptions used to create hypothetical distributions for proposed new supply chain offerings should be validated before and after use in the modeling framework to ensure accurate representation of the process.

6.2 Impact to Industry

Improving performance of temporal commitments to customers is a supply chain goal of many organizations. End-to-end cycle time classification and simulation are topics explored in other industries. Retail, high mix low volume manufacturing, and bio technology have explored differentiating a population and constructing simulations to better understand variability in the system. Historic applications in industry focus on short term identification of process improvement opportunities or feasibility of service level agreement parameters (Pydynkowski, 2015) (Luna, 2015) (Napolillo, 2014).

The modeling framework discussed in this analysis is adaptable and can provide both an end-to-end cycle time view while providing insight into the individual process steps. High mix low volume manufacturing can leverage this framework to identify time consuming processes that may tie up specialized equipment. The simulation results from the framework can also be helpful in exploring new logistics options. For example, a retailer may have a goal of having outbound logistics for ground shipping take two business days or less. Using the framework presented here, the retailer can compare the performance of branches with two day commitments or less to those with three or more to validate the goal's impact.

Dell, in general, is selling directly to the end user, making the delivery commitment the focus of the post simulation analysis. Other industries may be more concerned with other characteristics of the end-to-end process such as volume of frictionless orders or outlier performance to mean. The framework is robust enough to provide insight into these areas of concern.

6.3 Future Work

One short term area of opportunity is to find other product lines to repeat the success of this study's pilot project. Other desktop lines with similar supply chain flow paths are great candidates since direct shipment requirements will align to the previous efforts. To perform a similar project for Asia manufactured products, a deeper investigation into the consolidation facility and direct ship eligibility needs to be performed. This will require collaboration between the Order Experience Program Office, IT, and the functional teams that manage the Asia supply chain components. Key criteria driving the eligibility must then be mapped to criteria known at order entry, to allow for use in lead time calculations.

Another opportunity to mimic the success of the direct ship differentiation could be to limit certain product lines to be exclusively directly shipped or sent to a consolidation facility. This would ensure direct ship eligibility would be known at order entry, providing increased on-time performance. The trade-off for this would be less customization available to the customer. Further investigation into this offering and trade-off could be more useful for products that have complex criteria that dictate the direct ship eligibility.

Expanding on the statistical screening and population separation from this study, machine learning could be leveraged to perform a more robust analysis of all Dell offerings. A machine learning approach could provide a more real time analysis of the order cycle time data and investigate supply chain options that were ignored by this study for simplification reasons. Decision tree algorithms provide a more robust analysis of the entire order population, compared to the framework presented in this study that makes many simplifying assumptions that ignore smaller order populations.

A classification and regression tree (CART) approach can provide insight into generating accurate EDD values for the entire order population. This supervised learning approach can incorporate both categorical and numeric variables. The order population is iteratively split in half based on available variable characteristics until a minimum threshold of data points per population is reached. Each split can use a greedy approach, producing locally efficient decisions, to minimize the error in each leaf of the tree since making global decisions may be too complex. Once the population is organized in the tree, the individual populations can be analyzed. The algorithm can also be paired with a cost of complexity function, introduced by Breiman et al., that eliminates branches that do not add much value to the overall model. Maintaining the appropriate level of complexity is important for matching results with system capabilities and socializing the analysis results with the rest of the organization (Wilkinson, 2002).

Dell is utilizing a supervised machine learning algorithm within the Business Transformation Program Office (BTPO) analytics team. The approach takes an end-to-end view without individual process steps broken out. The BTPO approach works well for analyzing the current state supply chain offerings, but in its existing form does not have a method to incorporate process improvement or new supply chain offerings. Altering the BTPO machine learning approach to include individual processes would include the benefits of this study's approach and machine learning.

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