Using Process Analysis and Simulation to Evaluate the Process Capability of an Order Processing and Fulfillment System

by

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Submitted to the MIT Sloan School of Management and the Engineering Systems Division in partial fulfillment of the requirements for the degrees of Master of Business Administration and Master of Science in Systems Engineering in conjunction with the Leaders for Global Operations Program at the Massachusetts Institute of Technology June 2015

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Abstract

In order to compete with online retailers that offer same-day shipping, Dell is looking to implement a Same Day Ship (SDS) program for their SmartSelection products (in-stock, build-to-stock products) in the US. Currently, Dell offers Next Business Day shipping (NBDS) for these products and wants to assess the capability of the existing processes to reliably execute the faster cycle times required for same-day shipping.

Ship date commitments to customers are made based on specific order characteristics (such as payment type and in-stock availability) and on-time performance is evaluated based on whether these commitments were met. Historically, “on-time” was considered orders that were shipped on their estimated ship date or earlier and consequently processes and systems evolved around these goals. Current metrics indicate a significant opportunity to offer an earlier ship date to customers but a detailed process assessment was necessary to enable fact-based decision-making.

This thesis examines the process capability of Dell’s payment processing and order fulfillment processes in order to assess the risks and make informed decisions related to expanding a Same Day Ship (SDS) program. Research was conducted by observing current processes, analyzing historical data and participating on a Same Day Ship pilot launch. Simulation modeling was then used to evaluate and understand how changes to the individual processes would affect overall performance.

Analysis of historical data shows high volatility in Dell’s current processes, indicating that a full-scale Same Day Ship program would not be successful without process improvements. Results and observations from the Same Day Ship pilot, however reveal that under certain conditions, a same-day ship commitment can be met with over 95% reliability. The differences in these results can be attributed to process improvements that reduced variation as well as focused commitment on behalf of the pilot team.

Finally, simulation and scenario modelling show that on the full volume of product offerings, improvements greater than 75% to the mean and standard deviation in both payment and fulfillment will be necessary in order to ensure a consistent same-day ship performance of over 95% without substantial prioritization.

This framework can be extended to other areas of business in which cycle time is a key metric for process performance. Using a multi-dimensional approach to evaluate process capability can offer insights into highly variable systems that traditional process capability analysis will not allow.

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1 Same day shipping refers to when the order is shipped from the fulfillment center. Delivery time after the order is shipped depends on the shipping rate selected by the customer.
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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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1 Introduction

1.1 Background

1.1.1 Dell

In 1984, with a vision for “how technology should be designed, manufactured and sold”, Michael Dell founded what is now Dell Inc. in his dorm room at the University of Texas, Austin (Dell Inc., 2015). Customer experience was established as a key differentiator and allowed Michael and the team to grow the business by almost 80% annually (Dell Inc., 2015). Throughout the ‘90s Dell continued to grow in the US while also expanding its operations globally and launching Dell Inc., 2015, setting new standards for ecommerce worldwide. By the 2000s, Dell became one of the highest-volume ecommerce sites as well as the No. 1 computer manufacturer in the world (Dell Inc., 2015). During this initial, rapid, growth phase, Dell sold custom computers directly to its customers using a just-in-time, build-to-order fulfillment model. This model allowed the company to respond to and fulfill unique customer needs but created an increasingly complex supply chain. Dell’s world-class supply chain management, however, operated successfully while maintaining strong customer loyalty as established in the early years. (Dell Inc., 2015)

With the advent of the PC becoming a low-price commodity in the mid-2000s and the prevalence of tablets and smart phones reducing demand for larger computing devices, Dell’s success did not remain on the same growth trajectory. In 2007, Michael Dell returned as CEO and developed a new strategy to focus on the business of becoming an overall IT solutions provider for its customers. This put in motion a number of changes to the company as a whole, from changing their product offerings to the way they did business in general.

1.1.2 The New Dell Business Model

The original Dell business model for PCs was focused on selling custom products direct to customers, offering an almost limitless number of configurations. This configure to order (CTO) model, gave Dell information on exactly what customers wanted, when they wanted it, satisfying
customer needs better than any competitors (Dell & Fredman, 1999). However, as globalization took hold, the combination of long lead times and lower margins caused Dell to need to rethink their strategy.

Therefore, the “New Dell Business Model” was developed. Dell would transition from an exclusively CTO model to a model that also offered build to stock (BTS) products that were held in inventory. Products sold from inventory are branded by their program name: “SmartSelection.” SmartSelection orders promise to ship out of the warehouse on the next business day (NBDS) if the product is in-stock and the payment is processed successfully. Customer experience is again at the forefront of the program with a marketing campaign that pledges products that are “Easy to order, easy to buy and easy to own.” (Dell Inc., 2015)

Over time, the percentage of build-to-stock products sold through a variety of channels would increase. This change means significantly transforming the business model and the resulting supply chain. Most notably, Dell will now need to build the capabilities to hold and manage finished goods inventory and in particular, compete with competitors that have been using this model for years. Also, by promising customers to ship products by the next business day, Dell faces the challenge of processing payments and fulfilling orders in much shorter cycle times. In an effort to maintain a positive customer experience, expected internal lead times contain buffers to absorb the variation within their process and ensure products will not be late to customers.

As the volume of BTS products as a percentage of total volume increases from 0% in early 2013 to an end state goal of approximately 60% for commercial products and 80% for consumer products, more and more customers will be experiencing the New Dell Business Model and the importance of getting it right is becoming even more prevalent.
2 Project Motivation

2.1 General: End to End Order Experience

Over years of growth, many different systems and processes emerged creating significant complexity in the ordering and communication process. The way orders are entered to the information that is communicated to customers varies significantly depending on the location, customer type, product characteristics, etc. This complexity creates many opportunities for defects and subsequent opportunities for a suboptimal customer experience. As Beckman & Rosenfield (2008) stated in Chapter 7 of Operations Strategy: competing in the 21st century, the customer often does not have a view into the mechanics behind the fulfillment process and how the different organizations and systems work together, nor are they interested in hearing why the process didn’t perform as promised. “The entire order fulfillment process must work smoothly across functional boundaries to serve the customer” (Beckman & Rosenfield, 2008, pg. 273).

For example, over 70% of orders arrive earlier than their estimated delivery date, forcing customers to receive their products before they intended, creating issues at business that aren’t ready for deliveries or even risking theft if products sit unexpected on doorsteps.

In order to succeed in today’s markets, Dell recognizes that it must return to its original cornerstone of great customer experience as a differentiator. As such, an End to End Order Experience program consisting of eight different workstreams was created with a primary objective to improve the overall customer experience. The workstreams are led by executives across many stakeholder groups and include but are not limited to, a metrics tracking and analysis team, a team to focus on setting lead times accurately and a team to improve how many defects are present in the initial order entry process.

The customer experience includes any interaction with the customer from the initial shopping period through order delivery and payment (Figure 2-1).
In addition, the key performance indicator (KPI) instituted and tracked by the program is consistent with a common industry benchmark known as the Perfect Order Index (POI). According to Columbus, (2008) the perfect order isn’t just for supply chains anymore. Companies taking a customer-driven supply chain “approach must define dashboards and scorecards that go beyond just measuring their own activity and contributions. To drive the greatest value, companies must instead focus on measuring the accuracy, speed and permanency of change they bring to each other through collaboration. The Perfect Order Index is one metric that captures the effects of collaboration on supply chain execution and fulfillment” (Columbus, 2008, pg. 37). This index measures four components of each customer order: on time, complete, damage free and accurate documentation (Figure 2-2).

**Figure 2-2 Industry benchmark metric for perfect order index**

In a benchmarking survey conducted in 2007 of the consumer electronics industry for build to stock products, the median perfect order index was 65.9% and the best was 82.6% (Hofman, 2010). Dell’s performance ranks slightly above the median for this study.
An initial analysis of the perfect order index showed that the percent on time would be the most significant driver of the metric with the greatest opportunity for improvement. Overall, only 20% of BTS orders arrived to the customer on the committed date (about 70% were early and 10% were late, see Figure 2-3)

![Figure 2-3 Actual delivery minus expected delivery for BTS orders. Negative values indicate orders that were delivered before the promised EDD.](image)

In comparison, configure to order (CTO) products also have a similar profile where more than 90% of products are early and less than 6% are late. However, for the purposes of this project, subsequent analysis focuses only on the BTS products in the system, simplifying the processes under consideration.

### 2.2 Specific: Same Day Ship Program

With 70% of orders arriving early to customers, there appears to be an opportunity to reduce the order shipment and delivery time forecast and compete with companies that currently offer faster and more predictable ship dates. Egan writes about “Same-day Insanity” as Target joins the pool of retailers that are quickly trying to catch up to the likes of Amazon and Google that are offering same-day shipping as part of their model to increase sales and boost profits (Egan, 2014). Companies are looking for ways to get ahead and offer more services that meet customer expectations. Considering the perfect order index, the orders that are consistently shipped early become an opportunity for Dell to communicate earlier delivery dates and improve the percent on-time metric.

In addition, approximately 43% of BTS orders actually ship out of the warehouse on the same day they are ordered, regardless of the expected lead time that was communicated to the
customer. Considering this information, another workstream under the Order Experience umbrella is the “Same Day Ship” program, charged with determining how Dell could transition to committing to shipping products on the same day they were ordered. This includes understanding which subset of products, product characteristics or volume could be offered as SDS to customers with reliable ship date estimates.

The challenge of implementing such a program, however, is determining, based on available data and resources, if the current processes are capable of achieving these new targets.
3 Hypothesis

The hypothesis proposed in this thesis is that a framework consisting of historical data analysis, a pilot case study, and simulation can be used to better understand and manage variability. In particular, insights gained from these analyses can be used to make decisions related to whether or not the implementation of a program like Dell’s Same Day Ship program could meet the targets desired by the Company.

This thesis examines the current process capability of Dell’s order processing and fulfillment systems using this framework in order to assess the risks to customer experience of implementing a same day ship program.
4 Research Methodology

4.1 General Approach

The general approach to research and understand the current process capability of Dell’s order processing and fulfillment processes consists of using a combination of qualitative and quantitative data and techniques.

a. Understand current state processes and analyze historical data

The first step of understanding the process capability of Dell’s systems is to understand the processes in general. Process mapping is used as a tool to understand different levels of the processes. This is critical in defining scope and process boundaries by identifying the processes and organizations that will be included for analysis. It also involves understanding general process steps, decision points, and key data collection points (Cachon & Terwiesch, 2013).

Historical order data is collected from a number of different systems that store information about different segments of the process. With an understanding of the process steps and data collection points the right data can be collected for analysis.

Data is then analyzed to look for trends, approve or reject hypotheses, or support other findings. Parsing the data into subsets is often the most efficient way to perform an analysis. In particular, the purpose of analyzing the data in depth is to understand the distributions of different subsets of data in order to draw conclusions. Process capability is first assessed based on historical order data and key assumptions about the commitments made to customers.

b. Observe the SDS Pilot as a case study

As part of the Same Day Ship program, a pilot was conducted to test process improvements and IT changes. Observations and data collection from this process serve as a case study to understand the impact of such changes and assess process capability under certain conditions.

c. Simulation modeling
Historical data is used as the basis to build a monte carlo simulation model of the order processing and fulfillment processes and their interactions. A baseline model is created to replicate current observations of the system and ensure goodness of fit. Then, scenario modeling is used to test different circumstances of process improvement to better understand the impact to the overall system and distribution of cycle times.

d. Synthesize key learnings and draw conclusions

By combing learnings from current processes, historical data, a case study, and simulation modeling conclusions about process capability for implementing a Same Day Ship program can be drawn. This becomes a framework for which to analyze process capability in similar processes and systems.

4.2 Data Collection: Sources and Limitations

Data for this research was collected through a variety of sources, both quantitative and qualitative.

Quantitative data is compiled through multiple order management systems and organized by order number. Data is mostly complete and available for orders in the BTS system however legacy systems created for old processes are still used to capture data points for new processes. As such, field headers do not always represent the data exactly and confusion occurs between groups that have access to retrieve and analyze the data. Blank or null values occur in the database, often invalidating close to 20% of order data. In addition, excess and redundant data clouds analysis and can create different opinions or analyses for those that interpret the data differently. Files are generally too large for most standard issue laptops to process without special software or tools.

The data available is a mix of customer, product and process information including detailed timestamp values for key, but high level, process steps. Some information on payment processing holds or other issues that delay an order is available. However, data describing lower level processes is intermittent and largely unavailable. For example, data to segment the
fulfillment process or understand how long it takes the Fraud team to investigate an order could not be retrieved and a qualitative assessment was necessary.

Qualitative data was collected by a variety of means: attending meetings, participating on project teams, visiting the fulfillment center, shadowing employees at work, conducting interviews with key stakeholders and studying process documentation.
5 Research Analysis

5.1 Introduction

5.2 Current State Processes

To understand the process capability of Dell’s systems, a brief introduction to the context of the current state processes is necessary. Lead times are set internal to Dell and are based on order characteristics at the time the customer places their order. Characteristics such as payment type, product type and requested delivery speed (express versus ground shipping) determine the expected lead time. The lead time is then a summation of expected payment processing time, fulfillment time, and delivery time based on those characteristics. Once the order is placed, the lead time is communicated to the customer as either an estimated ship date (ESD) that is based solely on payment and fulfillment or an estimated delivery date (EDD) that includes all three. These dates become the specifications limits to which Dell must perform. Figure 5-1 illustrates how information provided by the customer relates to Dell’s estimated lead time calculations.

![Figure 5-1 An illustration showing the relationship between customer order information and Dell’s internal lead time calculation]

For the purposes of this project, only the processes up to and including the ESD are considered for analysis. At checkout, customers can chose to select express delivery or ground delivery and the associated lead times are different. However, since this thesis considers the process capability for same day shipping and ignores delivery times, the delivery process is out of scope.
Delivery information, however, is important since the type of delivery requested determines the shipment cutoff time for fulfillment.

The payment processes begins when an order is complete within Dell systems and ends once Dell has enough information to ensure the order and payment method are valid. Order fulfillment begins only once payment processing is complete. The fulfillment process ends once an order is on a truck for shipment. Therefore, these two processes are performed independently, in series. The following sections describe the payment and fulfillment processes and then discuss how lead times are set for each of these processes.

5.2.1 Payment Processing

The payment processing process consists of a combination of manual and automatic steps routed through multiple systems and stakeholders (both internal and external) as an exception-based process. Order characteristics determine which orders must be held for processing and consequently which groups need to get involved in order to approve the payment. For example, if an order appears fraudulent, a fraud hold is initiated and the order is circulated to the fraud team for investigation. Depending on the payment method, customer type or any number of data points collected at order entry, over 50 different types of holds may be placed on the orders before approval.

Each of the stakeholders manage queues based on the type of work they are performing. For example, the Fraud team processes orders by the level of risk calculated by detailed algorithms and historical data. The credit card authorization team processes orders first-in, first-out (FIFO). In addition, each stakeholder has a service level agreement (SLA) defined for the expected processing time of each order. In some cases, holds have automatic release settings once they have been in a queue for a certain period of time.

If Dell’s systems do not detect any issues with the order, the payment is processed and passed through to the fulfillment teams in a matter of minutes. For NBDS eligible orders, over 50% are processed without any significant holds and take less than 20 minutes. The remaining orders that
must be processed with manual intervention vary significantly and can take anywhere from 30 minutes to more than 10 days depending on the process that’s required.

5.2.2 Fulfillment

The BTS fulfillment process is contracted to a third party and all US orders are processed through one of their three facilities: Nashville, El Paso, or LA. Once the order is through the payment process, Dell’s IT systems route the order to the most appropriate facility depending on location and inventory availability. After the order is downloaded into the fulfillment center’s systems, the order is placed in queue and waved into production based on the current utilization in the fulfillment center.

Fulfillment begins once order identification labels for each order are printed. These labels are then walked to the location of inventory that matches the product listed. Workers at the inventory locations place these labels on the matching products and place them on the conveyor system. Once labeled, the products can be routed to a rework carousel, a station to pack or repack with other accessories, or the loading dock to either be shipped as parcel or packaged on a pallet.

Inventory is managed within the facility or in a neighboring building as active and inactive. Active inventory is inventory staged at the point of use (near a conveyor) where order identification labels are applied. Inactive inventory is kept at a location far from the conveyor belts until it is needed. If there is not enough active inventory to complete an order, the materials replenishment process begins to bring inactive inventory to an active position.

For NBDS orders, the fulfillment centers operate with an SLA to complete each order within 24 hours from the time it downloads until it is scanned for shipment. Approximately 25% of orders that are promised as NBDS orders are processed within 5 hours. The remaining orders take anywhere from 5 hours to more than a month with significant variation.
5.2.3 Setting Lead Times

Total lead time from order entry to ESD is calculated by adding the expected payment processing lead time (as an integer value in days) to the expected fulfillment lead time (also an integer in days). This number is then added to the current date/order entry (OE) date (excluding weekends and holidays) to return the ESD that is communicated to the customer (See Figure 5-2 for an example calculation).

\[
\text{Estimated Ship Date (ESD)} = \text{OE Date} + \text{Payment LT (business days)} + \text{Fulfillment LT (business days)}
\]

Figure 5-2 Diagram illustrating how estimated ship date and estimated delivery date are set

The payment processing lead time is set based on a combination of the payment type and the company number (over 1600 unique combinations) and comes from a lookup table that is periodically reviewed and updated based on historical order cycle times.

The fulfillment lead time for BTS products is derived based on the inventory level of the product that is being ordered. If the product is in-stock with ample inventory then the fulfilment lead time is 1 business day (i.e. the fulfillment team must be held to their 24 hour SLA) and the product is marketed as a Next Business Day Ship (NBDS) item. If the inventory drops below 2 days of inventory, the lead time is automatically extended based on the expected time to replenish the stock and the product is no longer marketed as NBDS. This database of fulfillment lead times is updated automatically by Dell’s systems and manually by employees on the fulfillment team.

Both the payment and fulfillment lead times are calculated independently and added together without regard for any potential correlation between the two processes or other factors such as the time of day or day of week; however all lead times account for only business days.
As discussed previously, orders that are promised to ship next business day must meet the lead time criteria of a payment lead time of zero days and a fulfillment lead time of one day at the time of checkout. Once these lead times are set and the ESD is communicated to customers, Dell’s performance is measured by its ability to hit the ESD target.

The distribution of lead times (from order entry to estimated ship date) for BTS products is shown in Figure 5-3. Over 68% of orders are promised as NBDS (estimated to ship next business day and then communicated to the customer as such) and the remaining have a shipment LT range from 2 to over 100 days.

![BTS Lead Times (Days)](image)

**Figure 5-3 Distribution of lead times assigned to BTS orders**

5.2.4 Historical order analysis

Process capability for Dell’s order processing and fulfillment processes was assessed by examining the current performance of the NBDS program as well as the performance of hypothetical SDS eligible orders. The process was also broken down and analyzed by its two major components independently: payment processing and order fulfillment.

Examining the subset of SDS eligible orders in historical data allows an understanding of process capability and variation for a representative sample of the types of orders that would be
considered for the SDS program. Therefore, to determine hypothetical SDS eligible orders, and for the purposes of analysis, subsets of data were defined (See Figure 5-4) based on the lead times assigned at order entry. Within the population of BTS orders, the data was first separated by orders that were in stock (fulfillment LT of 1 day) and orders that were not in stock (fulfillment lead time greater than 1 day). From there, orders that were eligible for NBDS were determined by the expected payment LT. SDS eligible orders are those that meet the criteria of an NBDS order but are entered into Dell’s system before 2 p.m. on a weekday.

![Figure 5-4 Subsets of BTS orders](image)

**5.2.4.1 Overall process**

Within the BTS system (products that are theoretically always in stock and should be available to ship by the next business day), ESD lead times in the data have a range of 1 to 103 business days (or 1-143 calendar days). The standard deviation for these lead times is about 6 days, indicating significant variation in the lead times that are set and predicted within Dell. In comparison, the actual cycle time for the same process ranges from 0 to 48 calendar days (or 0-34 business days) with a standard deviation of about 2.5 days. Also, for many of these orders, if Dell’s systems predict a lead time of greater than 30 days, the customer is notified that the order will be canceled. These discrepancies highlight the fact that Dell’s lead times do not accurately reflect...
the performance of the processes they are designed to predict. This is important since order eligibility for NBDS or SDS is determined primarily based on the lead times set at order entry.

The lead time process itself creates variance and uncertainty. Lead times require the coordination of multiple systems and different organizations along the end to end order fulfillment process, meaning different owners in each part of the process use, interpret and maintain systems and processes in different ways. In addition, since lead times are calculated from relatively static look-up tables based on order characteristics, any changes to these tables will influence the distribution of lead times and the resulting performance targets for Dell’s processes.

Within the systems, constraints on the type of data and the way lead times are estimated also adds variation. For example, the lead times are set as integer values in days, so an order entered at 10:58 a.m. and one entered at 10:58 p.m. both need to be processed by the end of the day. The order entered in the a.m. has 12 hours more available processing time than the one entered in the p.m. This creates challenges for analyzing process cycle times and trying to create consistency in order to achieve more predictable cycle times. Managing a process with varying cycle time requirements based on the time of day creates complexity for both supervisors and employees. With these constraints in mind, over 65% of all BTS orders are given a 1 day lead time, and are therefore part of the NBDS program. Regardless of how accurate the lookup tables are and the time of day the order is entered, a large percentage of orders are subject to the NBDS requirements and performance is measured.

A comparison of the NBDS cycle time distribution and the SDS eligible cycle time distribution is shown in Figure 5-5. As discussed previously, SDS eligible orders are used as a baseline to understand potential process capability for an SDS program. By removing orders entered after 2 p.m. and on weekends, the distribution statistics improve slightly but not by an amount that would prove success of a SDS program. With a standard deviation close to a full day for both subsets, it’s clear that an SDS program using these processes would not be able to reach the 95% success target.
Regardless of the variation, the NBDS program still operates above 90% performance as defined by Dell’s internal key performance indicators (KPIs), meaning more than 90% of orders are shipped to customers on or before the estimated ship date, without regard to the ship cutoff based on delivery speed. In the second quarter of 2014, the overall performance was 94% with 38% on time and 56% early. Approximately 37% of all NBDS orders were shipped on the same day by the required truck cut time.

Considering the SDS eligible orders from Q2, performance to the hypothetical SDS cutoffs would have been about 61% on time. Given the fact that SDS eligible orders are determined by an earlier order entry time and thus have more time for processing, one would expect that relative performance would be slightly higher for the subset of orders that arrive earlier.

The concept of an earlier order entry cutoff time for SDS eligibility as an opportunity to minimize risk to customer experience was also considered for analysis. The order entry distribution (“demand”) is not uniform throughout the day but it does follow a similar distribution day to day throughout the quarter (Figure 5-6a). The majority of orders (80%) arrive between the hours of 9 a.m. and 8 p.m. Since the processes operate in series, the demand faced by the fulfillment process is based on the output of the payment process. The demand seen by fulfillment follows a very similar distribution (Figure 5-6b).
On-time performance by order entry hour was analyzed to better understand if there was a time of day at which performance began to decline due to the fact that less time was available for processing and/or order volume was increasing. Considering an entire quarter of data, performance (to ESD) by hour for NBDS orders declines slightly as the day progresses (see Figure 5-7).

To understand the impact related to SDS, we can apply the SDS target to the same set of data and examine the performance over time. In this case (Figure 5-8), performance hovers around 75% on-time and then drops off significantly after 8 a.m. This indicates that restricting the SDS program to order entry time and day requirements will have a positive effect on the outcome but may not be enough alone to meet the expectations for customer order experience.
While order entry cutoff time is one opportunity to isolate orders that might yield a higher performance level, the program would still need to find other ways to predict more consistent cycle times. The data was segmented into numerous subsets (as defined by information collected at order entry) to determine if any other patterns in the data emerged as potential indicators of predictable cycle times. Unfortunately, the variation and relative performance in each subset closely resembled that of the parent population and no conclusions could be drawn from this analysis. For example, Figure 5-9 below shows on-time and late percentages for NBDS orders containing consumer and commercial products. Tablets and workstations have slightly lower performance levels than the other products. The tablet fulfillment process is slightly different than the other fulfillment processes because of additional packing requirements and a separate fulfillment area. The difference in performance for the commercial products is likely due to the larger order sizes for commercial orders. Overall, however, the performance for these subsets is relatively similar.
### On-time performance and relative volume for consumer (top) and commercial (bottom) products

<table>
<thead>
<tr>
<th>Product Type</th>
<th>Early</th>
<th>On-time</th>
<th>Late</th>
<th>% of Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Consumer Products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted Avg of Performance</td>
<td>93.6%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alienware Notebooks</td>
<td>60.00%</td>
<td>24.00%</td>
<td>16.00%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Fixed Workstations</td>
<td>50.45%</td>
<td>37.70%</td>
<td>11.85%</td>
<td>0.6%</td>
</tr>
<tr>
<td>Mobile Workstations</td>
<td>58.91%</td>
<td>29.42%</td>
<td>11.67%</td>
<td>0.9%</td>
</tr>
<tr>
<td>Personal Desktops</td>
<td>52.98%</td>
<td>40.44%</td>
<td>6.58%</td>
<td>17.9%</td>
</tr>
<tr>
<td>Personal Notebooks</td>
<td>58.72%</td>
<td>36.94%</td>
<td>4.34%</td>
<td>32.4%</td>
</tr>
<tr>
<td>Tablets</td>
<td>48.30%</td>
<td>40.72%</td>
<td>10.99%</td>
<td>11.5%</td>
</tr>
<tr>
<td>XPS Desktops</td>
<td>34.82%</td>
<td>58.92%</td>
<td>6.26%</td>
<td>3.9%</td>
</tr>
<tr>
<td>XPS Notebooks</td>
<td>48.42%</td>
<td>45.40%</td>
<td>6.18%</td>
<td>0.5%</td>
</tr>
<tr>
<td><strong>Commercial Products</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Weighted Avg of Performance</td>
<td>90.54%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cloud Client</td>
<td>67.54%</td>
<td>29.84%</td>
<td>2.62%</td>
<td>0.1%</td>
</tr>
<tr>
<td>EqualLogic</td>
<td>0.00%</td>
<td>0.00%</td>
<td>100.00%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Latitude</td>
<td>62.89%</td>
<td>25.80%</td>
<td>11.31%</td>
<td>10.8%</td>
</tr>
<tr>
<td>OptiPlex Desktops</td>
<td>56.80%</td>
<td>34.66%</td>
<td>8.54%</td>
<td>21.4%</td>
</tr>
<tr>
<td>PowerEdge</td>
<td>91.30%</td>
<td>0.00%</td>
<td>8.70%</td>
<td>0.0%</td>
</tr>
<tr>
<td>Software - Server and Other</td>
<td>100.00%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

While product type does not offer any insight into process variation, another aspect to examine was whether or not cycle time varied throughout the day. The hypothesis was that later in the day, orders would take less time to fulfill since employees would have to hurry orders along in order to ship by the cutoff time. Plotting cycle time as a function of order entry time showed no correlation between the two values and a plot of average cycle time by order entry time also appears relatively flat throughout the day (See Figure 5-10).
A sample control chart (shown in Figure 5-11) from one weekday in June also illustrates the amount of variation inherent in the process.

Overall, the process contains a large amount of variation and it is not clear that any particular subset of data can be isolated to reveal a process with much better performance than any other. Therefore, analyses of the payment and fulfillment processes follow.
5.2.4.2 Payment

The payment process distribution is characterized by the majority of orders taking less than one hour, approximately 10-15% taking between 1 and 6 hours, and then a long tail extending out to as many as multiple days (Figure 5-12). In general, if an order is processed automatically, it takes less than an hour but if manual intervention is required then duration is extremely variable. It is important to note that even with the large variation, over 93% of payment orders meet their same day cycle time for the NBDS process.

![Cycle Time - Payment (Hours)](image)

**Figure 5-12 Cycle time distribution for Payment Processing**

For SDS eligible orders, approximately 80% are processed within one hour and 92% were processed by 3 p.m.

As it gets later in the day, a higher percentage of orders begin to miss the cutoff. In addition to the normal variation within this process, this can be attributed to having less time available for processing as well as a higher volume of orders coming into the system during these later hours.

Digging deeper into the payment data, a few patterns of cycle times become apparent. For example, there are clusters of orders that took less than 1 hour, approximately 1 hour, approximately 6 hours, and then others that took a multiple days. This indicates different processes within the data rather than a coincidence in cycle times. Figure 5-13 illustrates the stratification in cycle times within the payment process.
Figure 5-13 Control chart showing the different patterns of cycle time "levels" in the data

Approximately 12% of orders have cycle times close to 6 hours and nearly all of these are due to a fraud hold. Further inspection of these orders indicated that the holds were auto-released from the system after 6 hours. In other words, the order sat in the fraud queue for 6 hours (without being investigated) and after 6 hours the hold was released and the order was placed in production (for fulfillment). These orders were in the queue because the system flagged them "high risk" initially but their prioritization level once in the queue was not high enough to have been addressed before the 6 hour limit.

Another subset of data that defines a different pattern of cycle times is related to the payment type. For example, American Express credit cards, though representing less volume, have significantly less variation and lower cycle times than the other credit cards. This is usually due to different fraud characteristics and thus American Express cards spend less time in the fraud queue.

In general, for the orders that exceed cycle times of longer than one hour, typically only one or two holds are responsible for extending the time for processing. This is significant because it means that when an order must go through a manual process within payment processing, its cycle time is affected by that process on its own rather than the addition of variation from many
individual processes. Since the payment process is managed by queues and exception holds, there is opportunity to reduce the cycle times in each of these processes.

While long cycle times in the payment process are usually due to an order sitting in a queue somewhere until it is prioritized for processing, extremely long cycle times (on the order of days) are generally a result of waiting for a customer response from an inquiry about something like fraud. There are few mechanisms in the current payment process to determine, real time, the aging of orders. Except for one daily report at 9 a.m. employees are relatively unaware of which orders have been sitting in a queue longer than necessary. The systems that filter the orders for processing determine the order within the queue and employees respond to the queue as it is presented with an attempt to meet SLAs.

In summary, the payment process is affected by the variation inherent in each of the unique processes within the overall process. The lack of careful coordination between these processes only amplifies the variation and delays within the process.

5.2.4.3 Fulfillment

Similar to the payment process, the fulfillment process is characterized by significant variation. NBDS orders are subject to an SLA of 24 hours from the time the order is downloaded to the system to the time it is placed on the truck for shipment. In Q2, this SLA was met approximately 85% of the time and the standard deviation for the process was about 20 hours (Figure 5-14). The SLA attainment is worse than the NBDS performance levels because an order can miss the 24 hour fulfillment SLA and still be on time to the ESD if the payment process took less time than expected. Therefore, the fulfillment center generally benefits from a buffer. A buffer greater than 1 hour occurs with over 90% of orders and over 50% of the orders gain an extra 8 hours due to this buffer from the payment process.
The SDS eligible orders do not perform significantly better. Approximately 75% take longer than 4 hours and only about 89% of them are processed within the 24 hour SLA.

The fulfillment center uses a waving process to control the processing flow within the facility. If certain areas have high utilization, the system will hold orders and release a batch of orders that can be processed in a different location within the facility. Once a batch of orders is waved, it is processed FIFO. This waving process can add non-value-add cycle time to an order as orders may sit in the system waiting to be placed in production. This becomes a tradeoff between adding minutes to the cycle time while the order sits in the system or creating backlog and queues out of the production floor that add time in other ways.

Two other examples of variation within the processes are the “jackpot” process and material replenishment. The jackpot is the rework area where products end up if an issue is detected. Orders need to be addressed by workers and products can stay in this rework area for a significant amount of time depending on the issues with the order. The second, material replenishment, is the process by which inactive inventory is transferred to active inventory. This process can occur at any point during the production day but if materials replenishment is required in the middle of fulfilling an order, a significant delay in order processing is possible. The process requires workers to go find inventory and bring it to the active location. Once the
inventory is in its active position, the workers responsible for processing the order (i.e. putting the label on the box) must remove all the packaging materials to prepare the products for processing. Neither of these issues are indicated in the dataset and thus cannot be analyzed as a separate type of variation.

Finally, the last major source of variation before an order is shipped is the process of manifesting an order and declaring it shipped. Orders are scanned on to trucks as they are completed and are released for shipping only when the truck is full or at the daily truck cut time. This final batching process means that while orders may be shipped by their ESD and be considered on-time, cycle times can be greatly extended artificially in the data as an order waits for a truck to close at the loading dock.

Since the fulfillment process is managed by a third party, detailed data and insight into the process other than what was described above is unavailable. The batching and waving process as well as the rework (“jackpot”) process increase cycle time and variation but the extent is unknown with the available data. It is important to note, however, that more than 50% of orders take longer than 8 hours to fulfill, indicating that the fast cycle times required for same day shipping are not necessarily being achieved on historical orders and process changes will be necessary.

5.2.4.4 Conclusions

Overall, these analyses show that the processes (as performed in Q2) do not appear capable of meeting the SDS targets at a 95% performance level. At best, based on the available data, the current processes would achieve just over 61% on-time without any intervention. In addition, no subsets of data in the current process were discovered to outperform the larger population. The large amounts of variation indicate that predicting consistent cycle times for orders is nearly impossible given the current state.

One key issue, however, that has not been taken into consideration thus far is the fact that these conclusions are being drawn on historical data and hypothetical targets. Human behavior adds a
unique element to the problem and process cycle times could be greatly impacted by changes in policies. Since it is clear that lead times have even more variation than actual cycle times, a significant buffer has developed within the different organizations to allow for this extra variation without penalties. Simply introducing new targets that aim to remove this buffer could change processes and give results that cannot be seen or predicted in historical order data.
5.3 Case Study – Same Day Ship Pilot

5.3.1 Introduction

A Same Day Ship Pilot was implemented and observed as an internal case study to better understand how processes could perform based on new Same Day Ship requirements. During the six month internship, I was able to participate on the pilot core team and observe decision-making as the pilot progressed. I also had the opportunity to visit a fulfillment center and watch the SDS pilot process in action. The provided a perspective to the process that would not have been possible through simple data analysis.

Stakeholders and support personnel formed a team to develop and manage orders as part of a testing phase for the program. This team met frequently to design the pilot, make necessary changes to systems and processes and then manage the process when the pilot went live. A number of key decisions were made in order to ensure success: scope, performance targets, IT and/or process changes, resources, and ramp plan.

5.3.1.1 Scope

Only a select number of orders from the SDS eligible subset would be included in the pilot for testing purposes. Once there was proof of concept, the program could be extended to eventually include all SDS eligible orders as defined previously. For the Pilot, members on the team would select particular SKUs with relatively constant demand and sufficient inventory levels. This would allow the team to have more control over the volume of units affected by the program and be prepared to avoid stockouts and other fulfillment issues.

5.3.1.2 Performance Targets

The first step in defining the SDS program was defining the targets by which “on-time” would be measured. At the most basic level, an order in the SDS pilot would be considered on-time if its manifest (shipment) time stamp was before its respective end-of-day truck cut time. For orders that needed to be shipped express, the cutoff time was 6:30 p.m. and for orders that would be
shipped via ground the cutoff was midnight. The on-time to ESD metric, first and foremost, would define the success of the pilot, and in this case, a performance of 95% or better was the target.

In addition to measuring on-time performance, the pilot also set intermediate process goals: the payment process should complete all SDS orders by 3 pm and fulfillment should process all SDS orders (if received by 3 pm) by the respective truck cut times.

Similar to the NBDS program, these cut times created varying process cycle time goals. For example, if an order came in at 10 a.m. then payment had five hours to process, but if an order came in at 1:30 p.m. then the payment teams had 90 minutes to process the order.

5.3.1.3 IT/Process Changes

A number of IT and process changes were also required for the SDS pilot. Some changes would be permanent process changes that would affect all orders in the system while others were developed specifically for the pilot or for interim solutions until more permanent changes could be developed. Some examples of process changes include updating the refresh rate of monitoring tools so that orders that are on hold will be reported (and thus can be actioned) within 30 minutes. The same tool was also updated with the ability to create alerts for employees responsible for processing so that they can easily determine which orders needed manual intervention. As discussed in the previous section, before these two changes were in place, delayed orders would only appear in a morning report, once a day at 9 a.m.

In the fulfillment center, visual indicators were placed on orders that were part of the SDS Pilot so that workers would be aware of which orders needed to be processed quickly. Where there were natural queues in the process, prioritization was used to process these orders more quickly. These visual indicators would be key in order to train employees before the volume ramped to higher levels of production.

5.3.1.4 Resources

In certain areas of the process, key resources were dedicated to processing Same Day Ship orders. For example, the Fraud Team assigned resources specifically dedicated to find and
process SDS Pilot orders outside of their normal risk prioritization list. This meant it would be less likely that SDS orders would get stuck at the end of a queue due to a low fraud risk. In other areas, employees were dedicated to create alerts for teams or to follow up on orders that needed manual intervention. Resources were also dedicated to performing root cause analysis each week to understand why orders were not processed in the required time. This root cause analysis became the basis for additional process changes and training as the pilot matured.

5.3.1.5 Ramp Plan

The pilot process began as an internal pilot with specific consumer products in May of 2014. In other words, for the purposes of piloting, the team would attempt to achieve 95% success on the chosen orders but the ESD communicated to the customer would still be for NBDS. Over the next 2 months, the volume of this pilot would increase to further test the systems. In September, once IT systems were ready, a small pilot went live to customers and customers received a SDS ESD for the products that were included in the pilot. In November, volume for this external-facing pilot started at approximately 300 orders per day and would increase to over 1,000 orders per day by mid-January. Given the timing of this internship, the following analysis and results are based on the external facing pilot from September to November.

5.3.2 Pilot Results

The overall performance for the external facing customer pilot was greater than 97% on-time during this period. The average cycle time was approximately 6 hours while the standard deviation dropped to about 10 hours (Figure 5-15). This is a 59% reduction in mean and a 53% reduction in standard deviation from the SDS Eligible dataset.
The control chart (Figure 5-16) below shows the cycle times of SDS pilot orders from September to November. While the mean and standard deviation in this dataset is much lower than the SDS eligible orders from the original process, the coefficients of variation for both datasets are similar. This indicates that the amount of variation with respect to the mean is approximately the same in the current process as in the SDS pilot process. The pilot improvements removed variation and increased the speed of the process by removing significant dwell time and non-value add wait time but the underlying processes have not really changed. For example, orders still received holds that needed to be actioned and were still batched and waved in fulfillment but the wait time between any of these steps was minimized. Figure 5-16 shows the cycle times and coefficient of variation of SDS pilot orders in sequential order and Figure 5-17 shows a similar volume of SDS eligible orders over a similar time period from Q2.

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**Figure 5-15 SDS Pilot cycle time distribution**

**Figure 5-16 Cycle times of SDS orders during the pilot**
Figure 5-17 Cycle times of randomly selected orders from the SDS eligible population (in sequential order)

Specific dwell time improvements and process changes in both the payment and fulfillment processes contributed to the overall reduction of mean and variation seen in the pilot. The payment process was able to reduce both the mean and variation for SDS orders by about 30% while the fulfillment team reduced their mean and variation more than 68%. Figure 5-18 shows the resulting distributions for the payment and fulfillment processes during the pilot.

Figure 5-18 Payment and Fulfillment cycle time distributions for SDS pilot orders
These drastic improvements were made through the on-going effort of the SDS pilot team and their supporters. The team was able to identify major sources of variation within the current process and design a process around the current one that effectively eliminated nearly half of the existing variation.

As mentioned previously, the biggest reduction in cycle time and variation was related to dwell time within the process. By creating alerts and using heightened awareness for SDS orders, the team ensured, if it was controllable, that orders did not sit in a queue for any significant amount of time. These orders were no longer subject to the extra non-value-add wait time that existed within the current process. Specifically, the team used prioritization in areas where queues typically add the greatest amount of time. SDS orders were flagged in different ways throughout the process and were often processed before other orders that had a longer lead time requirement. In addition, the SDS pilot team consistently put in a lot of effort to ensure as few pilot orders were late as possible and their effort showed through consistently high performing metrics. This undoubtedly put a strain on workers as they were continuously under pressure to prioritize the SDS pilot program.

It is important to note, however, that the process still had a large amount of variation with respect to the mean. Most of the variation can be identified through understanding the process and the constraints on the system even though it is difficult to see the root cause in the existing data. For example, even with prioritization, if an order requires material replenishment in fulfillment, it will add additional cycle time as the fulfillment employees wait for materials to be returned to active inventory. If a customer needs to be contacted during the payment process, that time is still dependent on the response of the customer. In the pilot process, these orders will no longer sit unattended but there is still an element of uncontrollable variation from the perspective of needing to wait for the customer to respond. Finally, occasional “black swan” events occur and systems and processes break down for unforeseen reasons. The pilot process is not designed to be robust enough to handle these variations. For example, many of the processes are dependent on signals and alerts from IT systems; if any one of these systems becomes unavailable there is little anyone can do to recover the process until the system is back up and running.
5.3.3 Conclusions

The Same Day Ship pilot was extremely successful overall as a pilot program since the performance for this program was consistently better than the current NBDS program results. In general, this difference can be attributed to increased focus and attention to the specific orders targeted by the pilot enabled by key process and IT changes.

The key question remains, however: can this be replicated full scale, with the SDS eligible volume and order entry profile? And what would it take to make this happen?

5.4 Simulation Modeling

The final portion of research was based on using simulation as a tool to better understand how general process improvements in the payment processing and fulfillment processes would affect the overall distribution. In particular, Dell was interested in understanding how much of a performance improvement would be necessary in order to achieve the target results for same day ship.

5.4.1 Base Case

A baseline model was created to first understand how historical data can be used to model the current system. @Risk for Excel (2014, Version 6.3.1) was used as the tool to determine the best fit distributions and then to perform monte carlo simulation to test the goodness of fit for the overall distribution.

@Risk uses a number of different fit validation tests to assess how well the model distribution fits the input data: Akaike Information Criteria (AIC), the Bayesian Information Criteria (BIC), the Chi-Squared, Kolmogorov-Smirnov (KS), Anderson-Darling (AD) and Root-Mean Squared Error (RSMErr) (Users Guide, 2013). For the purposes of this analysis, only AIC, BIC, and Chi-Sq tests were considered. The AIC and BIC tests are helpful for model selection since they are used to evaluate model selection alternatives and consider the number of parameters of the fitted
distribution. They are calculated from the log-likelihood function by the expressions in Equation 5-1:

\[ AIC = 2k - 2ln \, L \]
\[ BIC = k \, ln \, n - 2 \, ln \, L \]

Where \( L \) is the likelihood function, \( k \) is the number of parameters estimated for the fit, and \( n \) is the number of sample points.

Equation 5-1 Expressions for AIC and BIC test statistics (Users Guide, 2013)

The Chi-Sq goodness of fit test is used as it was originally developed to test fit validation, whether a particular distribution is a good fit for the data. The expression for calculating the Chi-Sq statistic is (Equation 5-2):

\[ X^2 = \sum \frac{(N_i - E_i)^2}{E_i} \]

Where

\( K = \) number of bins
\( N_i = \) the observed number of samples in the \( i \)th bin
\( E_i = \) the expected number of samples in the \( i \)th bin

Equation 5-2 Expression for Chi-Sq test statistic (Users Guide, 2013)

To start, the process was first separated into three unique cycle time segments: payment processing, order download and fulfillment. Each of these segments were treated as independent processes with different distributions and thus could be modeled independently and added together to create an overall cycle time (Equation 5-3).
**Total Cycle time** = Payment processing cycle time + order download cycle time + fulfillment cycle time

Equation 5-3 Expression for total cycle time of orders in the payment and fulfillment system for the SDS simulation model

For the purposes of Dell’s metrics, the order download cycle time is typically included in the fulfillment cycle time and is generally insignificant with respect to overall cycle time. However, occasionally an event occurs in which these cycle times are long and uncontrollable. As such, they are modeled as separate distributions for this model.

The payment processing cycle time distribution is best approximated by the inverse gaussian distribution with parameters mean \( \mu \) and a shape parameter \( \lambda \). All three of the fit statistics ranked this as the best fit distribution.

The variance is expressed as:

\[
\text{variance} = \frac{\mu^3}{\lambda}
\]

Equation 5-4 Expression for variance in an inverse gaussian distribution with mean \( \mu \) and shape parameter \( \lambda \)

Its density and cumulative distribution functions are described in Equation 5-5 and Equation 5-6.

\[
f(x) = \sqrt{\frac{\lambda}{2\pi x^3}} e^{-\left[\frac{\lambda(x-\mu)^2}{2\mu^2x}\right]}
\]

Equation 5-5 Density function for an inverse gaussian distribution

\[
F(x) = \Phi \left[ \sqrt{\frac{\lambda}{x}} \left( \frac{x}{\mu} - 1 \right) \right] + e^{2\lambda/\mu} \Phi \left[ -\sqrt{\frac{\lambda}{x}} \left( \frac{x}{\mu} + 1 \right) \right]
\]

Equation 5-6 Cumulative distribution function for an inverse gaussian distribution
Where \( \Phi(z) \) is the cumulative distribution function of a Normal(0, 1), also called the Laplace-Gauss Integral

**Equation 5-6** Cumulative distribution function for an inverse gaussian distribution

The distributions of download cycle time as well as the fulfillment cycle time can be best approximated using the lognormal distribution with parameters mean \( \mu \) and standard deviation \( \sigma \). This was also determined using @Risk software for the best fit. All three test statistics ranked the log normal distribution as the best fit for the download cycle time and both the AIC and BIC tests ranked it as the best fit for the fulfillment cycle time distribution. It was chosen as the fit distribution for both download and fulfillment in this model because its properties are well known and the parameters could be manipulated carefully in order to perform scenario testing.

The variance is expressed as:

\[
\text{variance} = \sigma^2
\]

**Equation 5-7 Expression for variance for the lognormal distribution**

Its density and cumulative distribution functions are described in Equation 5-8 through Equation 5-10:

\[
f(x) = \frac{1}{x\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\left[\ln x - \mu\right]^2 / \sigma^2}
\]

**Equation 5-8 Density function for the lognormal distribution (with \( \mu' \) and \( \sigma' \) defined in Equation 5-10)**

\[
F(x) = \Phi \left( \frac{\ln x - \mu'}{\sigma'} \right)
\]

**Equation 5-9 Cumulative distribution function for the lognormal distribution (with \( \mu' \) and \( \sigma' \) defined in Equation 5-10)**
\[ \mu' = \ln \left[ \frac{\mu^2}{\sqrt{\sigma^2 + \mu^2}} \right] \quad \text{and} \quad \sigma' = \sqrt{\ln \left[ 1 + \left( \frac{\sigma}{\mu} \right)^2 \right]} \]

**Equation 5-10** Definition for \( \mu' \) and \( \sigma' \) as referenced in Equation 5-8 and Equation 5-9

While cycle time is an important metric, it is not sufficient for modeling the system and determining whether an order was shipped on time. Thus, a fourth distribution, order entry start time based on the order entry distribution from Q2, was added to complete the model. By adding start time, the resulting distribution models the end shipment times of orders (Equation 5-11).

*End shipment time = Start time + Total Cycle time*

*(With Total Cycle time as defined in Equation 5-3)*

**Equation 5-11** Final expression for the SDS simulation model

For example, if an order is entered at 10 a.m. and has a total cycle time of 8.5 hours, then the output of the model for that particular order will be 18.5, meaning the order was shipped at 6:30 p.m. on the same day. If a different order was entered at 10 a.m. but had a total cycle time of 17 hours, then the output of the model would be 27, meaning the order was shipped at 3 a.m. on the next day. This allows us to model order performance with varying order entry start times.

The start time distribution does not confirm to common probability distributions and as such was modeled using historical Q2 data. The resulting density curve can be seen in Figure 5-19. This distribution estimates the probability of an order entered from midnight until 2 p.m., the cutoff time for SDS eligible orders.
Figure 5-19 Order entry distribution for SDS eligible orders

A key assumption in modeling this distribution is that the probabilities for orders during each hour is a discrete value, for example, an order entered at 1:01 p.m. has the same probability as one entered at 1:59 p.m. but is different than an order entered at 2:01 p.m. and these discrete probabilities were calculated as calculated as:

\[
\text{Probability of an order entered during the hour} = \frac{\text{Total number of orders entered between that hour during the second quarter}}{\text{Total number of orders entered in the second quarter}}
\]

Equation 5-12 Expression for probability of an order entered during a particular hour

The @Risk software then interpolates between values in order to create a continuous distribution.

In general, an end shipment time less than 24 hours means that the order as modeled was shipped on the same day and anything greater than 24 hours was late. Since the shipment cutoff time for orders shipping via express is 6:30 p.m. (or 18.5 hours) then a portion of the orders that have a resulting shipment time between 18.5 and 24 hours could be considered late. This gives a range of potential performance for the hypothetical distribution. The portion late can be estimated based on historical proportions of express and ground orders but for the purposes of analysis, a range is used instead to describe potential performance.
A chi square goodness of fit test (Equation 5-2) was performed to test the goodness of fit of the resulting model distribution. The chi-square statistic calculated based on the actual historical shipment time data and the modeled shipment times rejects the null hypothesis that the model distribution is representative of the actual shipment times. However, a close examination of each of the probability distributions for the individual processes and the overall resulting distribution show fairly representative values. The model still provides an estimate in order to apply scenario testing to better understand the effects of process improvement changes in each of the stages. The following two sections describe two different test scenarios that were modeled to test assumptions about large scale process improvements within payment and fulfillment processes.

5.4.2 Scenario 1 – Improvements Similar to Pilot Results

The first scenario considers the resulting distribution of shipment times if both the mean and variation in payment and fulfillment are reduced by the amount seen in the SDS pilot. In this case the payment processing mean was reduced by 30% and the standard deviation reduced by 31%. The fulfillment mean was reduced by 68% and the standard deviation was reduced by 77%.

When these improvements are applied to the baseline distribution model, the resulting distribution can be seen in Figure 5-20.
Figure 5-20 Resulting shipment times from making improvements similar to those seen in the SDS Pilot

This results in a potential SDS performance between 80.2% and 92.3%. This would be a significant improvement over the baseline but does not ensure confidence that the program would be able to reach a 95% success rate. A more precise estimate could be considered by using the fraction of express versus ground orders to calculate the expected proportion of orders shipped between 18.5 and 24 hours that were on-time. In Q2, this percentage was approximately 54%. Applying this percentage to the simulated distribution the expected performance would be approximately 87% shipped on-time.

Overall, this is a conservative estimate given the fact that the baseline distribution also performed slightly worse than the historical data but even at the higher end, these improvements would likely only produce up to a 90% performance when considering the full dataset and current processes. The long tail on this distribution still drives the overall process metrics and lower performance levels. Process improvements specifically targeted to reducing this long tail would go a long way to improve the consistency in performance levels for the program.
5.4.3 Scenario 2 – Improvements to Achieve Target Performance

The second scenario considered here is one potential scenario that would allow the program to reach 95% performance with a high degree of certainty. This target requires a much larger scale of process improvement. Both payment and fulfillment would have to reduce their mean and variation by over 75%. For the payment process, this would mean the standard deviation would be about 2 hours while the standard deviation for fulfillment would be slightly over 3.5 hours. The means would have to be reduced to approximately 0.5 hours and 2.5 hours for payment and fulfillment, respectively. Essentially, reducing variation would mean eliminating much of the long tail that was representative of the baseline and SDS pilot process.

Figure 5-21 Resulting shipment times distribution for implementing process improvements that allow the program to reach 95% success

The resulting performance (Figure 5-21) could range between 91.2 and 97.2%. Applying the same proportions of ground shipment orders as was discussed in the previous section, the performance would likely be close to 94.5% putting it in the range of a successful program as defined by Dell’s expectations.
5.4.4 Considerations

There are a number of considerations to understand before drawing detailed conclusions in response to the simulation models. First, the case study showed that human intervention can have a large effect on a process, particularly when targets are set to govern the process and extra resources are assigned to achieve high performance. These simulations models do not specifically address the changes in the distribution that would occur due to a change in process or attention from human intervention. They are based solely on adjustments to the baseline model assuming that a shift in variation and mean are possible while the distribution remains the same.

In addition, the model assumes independence in for each of the four input variables. In the current processes this assumption is valid since once an order is in a particular phase of the process little attention is paid to the time the order was placed or the time an order must be shipped. However, one of the major changes in the SDS pilot was closer order tracking and prioritization, especially as orders were getting close to their targets. This would invalidate the independence assumption since the performance in one part of the process would likely have an effect on the performance in the next part of the process.

The other consideration of importance to Dell is the practical aspect of the improvements modeled in each scenario. The question remains of how these modeled improvements might be translated to actual process improvements within the organization. The simulation model will not provide that answer but rather a framework for understanding the magnitude of improvements needed.

Therefore, as was the case in the previous two chapters, simulation alone is also not enough to determine the process capability needed to understand the potential success of a same day ship program. The final chapter will synthesize the learnings from each of the previous three chapters in order to draw conclusions and make recommendations related to implementing a same day ship program at Dell as well as using a similar framework for related applications.
6 Conclusions

6.1 Specific Recommendations

Setting Lead Times

The buffers built into Dell’s payment processing and order fulfillment processes have certainly contributed to inconsistency between lead times and cycle times. Predicting which orders should be offered as same day ship or next business day ship based on information at order entry is the first challenge. Removing the buffers from these lead times would allow for greater control in discovering which processes have actual variation versus which processes are using the buffer to their advantage simply because it is available. In addition, understanding upfront which orders would likely require a customer contact or which orders would suffer from an inventory issue in fulfillment would greatly reduce the long tail of “uncontrollable” variation. These orders could receive a lead time more in line with cycle time expectations.

Furthermore, current lead times and estimated ship dates are based on integer values. This greatly reduces the precision to which lead times and shipment dates can be estimated. For example, if the average payment cycle time for an order of 40 monitors paid for by Mastercard and shipped via express is 6 hours and the average fulfillment cycle time is 20 hours then today’s system would consider the payment lead time to be 0 days and the fulfillment lead time to be 1 day. If that order were to come in at 8 p.m., then it would have to perform better than its average cycle time in both payment and fulfillment in order to be on-time and make the shipment cutoff for the following day (22.5 hours later). If, instead, Dell’s systems were to calculate an ESD based on more accurate lead times, the ESD could be pushed to the following day to allow for an expected cycle time of approximately 26 hours.

Process improvements

Dell’s current processes contain variation at all levels. This variation leads to significant uncertainty when predicting lead times. Based on the available data, the variation is only marginally assignable depending on the process. For example, in payment, some variation can be attributed to different requirements within the fraud process but in fulfillment it is impossible
to discern the sources of variation. A detailed process analysis to understand specific sources of variation would help to identify which areas could be improved as well as have better estimates for lead time calculations. In chapter 10 of Matching Supply and Demand, Cochlan & Terwiesch (2013) discuss the importance of understanding the different types of variation occurring in processes and analyzing them using statistical process control techniques. Control charts allow for variation analysis and subsequent management of processes that are well understood. In addition, designing processes that are robust to variation can help in processes where variation cannot be eliminated entirely (Cochan, 2013)

The Same Day Ship pilot demonstrated that adding more stringent targets was powerful to reduce cycle times and eliminate unnecessary variation. Managing the processes by cycle time rather than variable cutoff times would allow for a more detailed understanding of process performance. For example, in current processes, variation is inherent in performance beginning from the time the order is entered. An order that is entered at 8 a.m. has 16 hours for payment processing while an order entered at 6 p.m. has only 6 hours for payment processing. By eliminating that variable requirement upfront, the process can be managed more carefully and variation in processing times can be measured and tracked more precisely.

The same day ship pilot also demonstrated that much of the dwell time in the current processes can be removed by more careful attention and prioritization. By applying many of the dwell time improvements instituted during the pilot, wait time could be minimized for the orders where it is most important. In addition to dwell time, other non-value-add activities can be identified and eliminated or reduced, thus reducing both variation and average cycle times.

A dedicated effort to identify and reduce specific variation in the processes would allow for much more accurate lead time predictions.

**Implementing a Same Day Ship Program**

Current data suggests that the processes in their current form are not capable of a 95% on-time performance rate. Implementing SDS with current processes would be detrimental to the perfect order index and would likely result in an increase in late orders as well as create a small
improvement in on-time orders. For example, if all SDS eligible orders from Q2 were part of the SDS program without any improvements\(^2\), the program would contribute about 40% of its volume to late orders. This would mean approximately 20% of BTS would be late, a 50% increase over the current volume of late orders. However, the Same Day Ship pilot program demonstrated success on a small scale and simulation modeling indicated that the performance target is achievable with large-scale improvements.

Given the results from the SDS pilot and simulation modeling, it appears that with significant, lasting process improvements and tools a SDS program could be successful for a segment of the NBDS population. It is critical that significant process improvements are implemented and process management is adjusted to support this program. Modifications to lead time calculations and systems would also enable more control over lead times and predictions and would be a beneficial first step to reducing variation.

### 6.2 General Implications for other firms/industries

Often, a firm must determine whether implementing a particular program or initiative will be worthwhile. Understanding its risks and benefits is challenging given the type of program and the data available. By using the framework employed here a better understanding of potential risks and challenges allows decisions-makers to make better decisions to ensure the success of their initiatives.

Careful analysis and hypothesis testing highlights current issues and potential areas of improvement. In particular, detailed examination of processes, especially processes within an end-to-end system need to be carefully understood in order to draw conclusions about how their decisions have impacted the system as a whole. For example, the Fraud process was developed around mitigating fraud risk to the company but was in direct conflict with the cycle time goals. Small changes such as how queues are managed could be implemented so that both fraud risk and cycle time goals are addressed without significant impact to either mission.

\(^2\) This considers only historical data and processes.
A carefully planned pilot study allows the company to better assess adjustments to processes that involve human behavior and intervention. This is an important area to study, especially if historical data is not available to understand the impact of metrics and other changes that will affect the way a process is performed. It is important to fully understand, however, the differences between current, pilot and potential future processes. For example, the drastic improvements seen in the SDS Pilot were mostly a result of extremely hard work and attention paid to the order within the pilot. This type of attention is not necessarily sustainable or realistic in a full-scale rollout of the program but it gives an indication of the upper limits of what the process could achieve given the current conditions.

Finally, simulation is an effective tool to model and test multiple different scenarios at low cost and low risk to processes. It provides an opportunity to visualize how changes affect overall distributions and what is necessary from a data perspective to achieve lofty goals.

Brought together, these three methods of examining a process allowed greater understanding of the process at hand and the risks that should be considered before implementing an extensive program such a Same Day Ship. In particular, in the retail industry where online shopping or e-commerce has become mainstream, companies may find themselves looking to move to the next level of service for their customers and trying to assess whether or not their processes can achieve faster targets. But also in general, companies with distinct and somewhat unconnected processing steps where success is measured by achieving cycle time goals can use this framework to carefully analyze potential impacts of new initiatives. It can be applied in just about any context where complex processes include human behavior and the resulting impacts are unclear.

6.3 Remaining questions for further research/future theses (Areas for future study)

An important question related to implementing the same day ship program is how to better predict estimated shipment time based on historical data and limited information at order entry. One of the biggest challenges that Dell faced was matching their lead times to cycle times and thus the excess variation meant on-time performance was not as high as it should have been. A
critical piece of work would be to better understand how to model lead times with such high uncertainty. In addition to predicting lead times for shipment, predicting lead times through delivery adds another element of complexity. Since delivery is ultimately what the customer cares about, a more accurate prediction model would have a significant impact on customer experience.

In addition to predicting better lead times, a deeper process analysis to determine true process capability at the lower levels of the process is critical. Research to determine the appropriate level of analysis for making decisions such as this could help to simplify and streamline the analysis process for faster decision-making.

Finally, process capability can be assessed in just about any industry and any context. A framework to assess process capability in general, applied to multiple different industries would permit for a more robust analysis for similar decisions at Dell and other companies.
7 Definitions

BTS – the selection of products that are built-to-stock, these products are eligible for either NBDS or SDS

Cycle Time – The actual time taken to complete Dell’s internal processes

EDD – Estimated delivery date as communicated to the customer, calculated as the addition of payment LT, fulfillment LT, and delivery LT

ESD – Estimated ship date as communicated to the customer, calculated as the addition of payment LT and fulfillment LT

LT – Lead time, the expected time (in business days) for Dell’s internal processes to complete

NBDS – Next business day ship, the program that is defined by products offered to ship out of the warehouse by the end of the business day following order entry

SDS – Same day ship, the program that is defined by products offered to ship out of the warehouse on the same day as order entry

SmartSelection – the subset of build-to-stock products that are in-stock at the time of order and advertised to the customer as such
8 References


