2017 SCM RESEARCH JOURNAL

Summaries of selected research projects by the 2017 graduates of the MIT Master of Supply Chain Management Program
Introduction


The projects included in this journal were selected from the twenty one projects submitted by the SCM Class of 2017 at the Massachusetts Institute of Technology. The articles are written as executive summaries of the master’s thesis and are intended for a business rather than an academic audience. The purpose of the executive summaries is to give the reader a sense of the business problems being addressed, the methods used to analyze the problem, the relevant results and the insights gained.

The articles included in this publication cover a wide selection of interests, approaches, and industries. These projects were developed in partnership with companies ranging in size from startups to the largest companies in the world. They cover industries as diverse as transportation, big box retail, semi-conductors, manufacturing, e-commerce, CPG, chemicals, pharmaceuticals, and logistics services. They address issues of drug security, consumer goods distribution, production planning, warehouse network design, inbound transportation, supply chain risk, demand forecasting, and inventory management.

Each of the projects is a joint effort between a sponsoring company, one or two students, and a faculty advisor. Companies who are members of CTL’s Supply Chain Exchange are eligible to submit their ideas for thesis projects in June and July and then present these proposals to the students in mid-August. In early September the students select which projects they will work on. From September until early May the teams conduct the research and write up the results. In late May all the sponsors, faculty, and students participate in Research Fest where all the research projects are presented.

The 10-month SCM program is designed for early to mid-career professionals who want a more in-depth and focused education in supply chain management, transportation, and logistics. The class size each year is limited to 40 students from around the globe and across all industries. The Master’s research projects give the students a hands-on opportunity to put into practice the learnings that they are receiving in their coursework.

We hope you enjoy the articles. The rest of the master’s research projects are listed at the end of this journal. You can also view all of the executive summaries on the CTL website at: http://ctl.mit.edu/pubs. If you would like to learn more about the SCM Master’s Program or sponsor a student master’s research please contact us directly.

Happy reading!

Dr. Bruce Arntzen
Executive Director, MIT SCM Program
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Predicting On-time Delivery in the Trucking Industry | 6

On-time delivery is a key metric in the trucking industry. If on-time delivery can be predicted, more effective resource allocation can be achieved. This research focuses on building a predictive analytics model, specifically logistic regression, given a historical dataset. The model yields significant resource reduction while incurring relatively small error. The interpretability of the model’s results can deliver value across many industries. Resulting cost reductions can lead to strategic competitive positioning among firms employing predictive analytics techniques.

Reducing Shipment Variability through Lean Leveling | 10

This research focuses on reducing shipment variability between manufacturer warehouse and customer distribution center. We used the leveling principle as defined by lean theory to create predetermined customer shipments for the top selling SKUs. We determined the optimal degree of lean leveling implementation through simulation analysis of various order policies. Sending frequent, small, recurring shipments on a weekly basis can improve service level, transportation cost, and cash flow.

Preemptive Solutions to Reducing Call Center Wait Times | 14

The security alarms services market delivers equipment and services to homeowners and businesses to monitor and enhance personal property protection. In this thesis, MIT partnered with a managed services provider specializing in complex, global service supply chain operations. To preemptively reduce the number of inbound customer calls, and thereby improve customer service, the thesis team followed a three-step process: customer segmentation, call center queue simulation (using inter-arrival times, service times, and number of agents), and preemptive solution development.
Production Planning with Complex Cost Drivers | 18

This thesis provides a new lot sizing model formulation for manufacturing firms that contract third party logistics (3PL) providers’ warehouses. The formulation extends existing models to account for the change in inventory holding costs depending on 3PL warehouse utilization. In addition, it provides a novel method for considering multi-tiered setup costs for products that share common setups. The new formulation produces production plans that reduce relevant supply chain costs for firms with these features.

Intermodal Variability and Optimal Mode Selection | 22

This research focuses on incorporating transit time variability into the transportation mode selection process. We identified a probability distribution for the transit time per unit of distance to quantify the impact of transit time uncertainty on inventory cost. Then we built a model that calculates the total logistics costs and compares the results for two transportation modes: intermodal and truckload. Results show that a particular lane is more likely to be assigned to truckload for high load values and/or high service levels.

Serialization of Prescription Drugs in the US: A Centralized View | 26

The 2013 Drug Supply Chain Security Act (DSCSA) of 2013 requires serialization of prescription drugs across the whole pharmaceutical supply chain. This thesis assesses the costs associated with serialization implementation on manufacturers and distributors/retailers. Taking the perspective of a centralized data model, we tested the feasibility of implementing a centralized database under both data nesting and unit level relational models. The findings suggest that serialization using a centralized data model would in all cases incur a higher proportional cost than using a decentralized model.

Balancing Product Flow and Synchronizing Transportation | 30

Traditionally, production and transportation planning processes are managed separately in organizations. In such arrangements, order processing, load planning, and transportation scheduling are often done sequentially, which can be time-consuming. Establishing a proactive steady flow of products between two nodes of a supply chain can bypass this order-plan-ship process. This thesis provides an analytical framework to calculate this steady flow. A steady flow of products can reduce transportation costs, increase cross-dock productivity, and reduce bullwhip effect upstream in the supply chain.
Predicting On-time Delivery in the Trucking Industry

By: Rafael Duarte Alcoba and Kenneth W. Ohlund
Thesis Advisor: Matthias Winkenbach

Topic Areas: Transportation, Predictive Analytics

Summary: On-time delivery is a key metric in the trucking segment of the transportation industry. If on-time delivery can be predicted, more effective resource allocation can be achieved. This research focuses on building a predictive analytics model, specifically logistic regression, given a historical dataset. The model, developed using explanatory variables with statistical significance, results in a significant resource reduction while incurring a relatively small impactful error. Interpretability and application of the logistic regression model can deliver value in predictive power across many industries. Resulting cost reductions lead to strategic competitive positioning among firms employing predictive analytics techniques.

Before coming to MIT, Rafael graduated with a B.S in Industrial Engineering from the Federal University of Rio Grande do Sul, Brazil. He then worked for Anheuser-Busch Inbev, having several roles in the Supply Planning & Performance Management team. Upon graduation, Rafael will join Bayer in Whippany, NJ.

Before coming to MIT, Ken graduated with a B.S. in Marine Engineering from Massachusetts Maritime Academy and then worked as an engineer aboard LNG carriers engaged in worldwide trade. He also worked for Transocean in the offshore Oil and Gas industry. Upon graduation, Ken will join GE Aviation in Lynn, MA.

Introduction

If firms could accurately predict the future with certainty, profits could be maximized and shareholders would prosper. Despite the complex nature of predictions, many mathematical tools exist that enable firms to do just that. As technology and innovation drive forward, methods facilitating the use of mathematical tools for predictions improve.

In the transportation industry, third-party logistic firms (3PLs) have a stake in making accurate predictions. A key metric by which 3PLs are measured on is on-time delivery. If on-time delivery could be predicted with some degree of certainty, then efforts could be focused on those loads that require resources. Currently, trucking firms commonly allocate resources to tracking and supporting each load tendered. This inefficiency and its associated costs represent a great opportunity for firms to gain a competitive edge, if corrected.

This research focuses on predicting on-time delivery in the trucking industry. Coyote Logistics, a Chicago-based 3PL, sponsored this thesis. With a high degree of data availability, we compiled an exhaustive list of variables potentially affecting on-time delivery. Through an extensive selection process, variables with high statistical significance were chosen. A predictive model selection process led to the choice of the logistic regression model.

Variable selection and data preparation

Selecting the right variables and predictive model requires a number of steps. A comprehensive understanding of the business operation enables the creation of an exhaustive list of potential variables. A brainstorming session with industry experts yielded the list of variables shown in Figure 1.

In addition to the list of variables, we also chose to use a binary decision variable for on-time performance. On-time for 3PLs is usually defined as within one hour of the appointment time. The time horizon used for the analysis in this thesis is two years. We determine this time horizon to be robust due to recency of the data and the inclusion of two calendar cycles. Data handling and preparation are critical to developing an accurate model. Through open lines of communication with our sponsor company, we classified data outliers.

Our dataset had more than fifty input variables, nominal and continuous, and one binary output variable. We looked to
identify, from the input variables, which combination would allow Coyote to predict on-time delivery. In the interest of reducing the number of variables that might yield better performance in the validation set, we used the stepwise regression approach. The stepwise approach enabled us to explore different combination of variables with a quick and flexible interface. Figure 2 presents the chosen six variables with high statistical significance for our model.

Multi-collinearity can play a role in distorting the results of a model by duplicating the statistical value through corresponding variables. We explored approaches aimed at identifying multi-collinearity and mitigating it. Of those approaches, principal component analysis, multiple correspondence analysis, and a correlation matrix were performed.

Through a systematic literature review, we identified three widely used models to predict categorical response using continuous and categorical predictors. The three models are logistic regression, neural nets and bootstrap forest. Due to Coyote’s desire for an explanatory model with high interpretability of model results, this thesis focuses on the logistic regression model. The neural nets and bootstrap forest models validate the selected model.

The dataset used presented a very imbalanced proportion of on-time and delayed loads. The small representation of delayed observations reflects the high service level that Coyote provides its customers. To develop a model capable of capturing the useful information that distinguishes the underrepresented class from the dominant class, we used stratified sampling. Stratified sampling is a method of sampling data used when classes are presented in a very unequal proportion in the original dataset.

Besides certifying a correct representation of both classes (0 and 1), it is also extremely important to avoid overfitting. This ensures that the chosen model is able to generalize beyond the dataset at hand. To mitigate this risk, we use the concept of data partitioning- dividing the stratified dataset into two groups: training and validation. The model is developed using the training set and evaluated using the validation set. The performance on the validation set provides insight into the model’s predictive power.

Performance evaluation

Once we developed and ran different models on our dataset, we determined how to measure the predictive performance of each. Different methods to evaluate a model’s performance can be used. Even though adjusted R squared is widely used, as the main goal of our model was to predict a binary outcome, we used a confusion matrix. The confusion matrix is a two-by-two table that classifies the actual response levels and the predicted response levels. The diagonal elements of the confusion matrix indicate correct predictions, while the off-diagonals represent the incorrect predictions.
Model results
Through misclassification rate is a widely used indicator of fit for the models, application of the model is a crucial consideration. Specifically, we considered the tradeoff between resource reductions and missed delayed loads. Missed delayed loads pose a serious problem for implementing the model. If the model predicts a load will be on-time and it is late without tracking, Coyote’s service level suffers. These missed delays are represented in the top right quadrant in the matrix. They represent the error for predicting on-time when the load is actually delayed. Because of the severity of consequences, emphasis is placed on minimizing this error.

While minimizing this error is critical, it must be balanced with a reasonable resource reduction. We quantify this reduction by dividing the number of predicted delays (0’s) by the total number of observations. In practice, this assumes that Coyote will track only those loads that the model predicts to be delayed. In the validation results presented in Figure 3, 23.6% of the loads are predicted to be delayed and should be tracked. We are not as concerned with predicting a delay that in fact is on-time. Since Coyote currently tracks all loads, tracking roughly 21% wastefully is acceptable in light of the significant resource reduction. Tracking a load that will be on-time also does not penalize Coyote’s service level in any way.

A new dataset was provided to test the robustness of the model. Figure 3 shows the comparison of the results from the Customer Test Data and the validation data.

Although the initial process of brainstorming variables through the fishbone diagram was exhaustive, we continued to search for additional data to improve the model. Despite some variables having a small enough p-value to be included in the model, we omitted them. The decision to exclude the new variables was substantiated by only a relatively minor improvement observed in the confusion matrix performance. Including variables with such small explanatory power under fabricated boundaries is forced. This leads to a less robust model. Since robustness is important in our model, we leave out variables with small explanatory power.

![Figure 2. Stepwise Regression for Variable Selection](image)
Conclusion

In predictive modeling, where a binary response is required, misclassification is the overall metric of choice. Predictive models can be tailored to optimize other, more specific metrics. For a company that focuses on achieving a high service level, the minimization of missed delays is critical. As the rate of missed delays decreases, the sensitivity of the model increases. The reaction of the model to increased sensitivity is a higher misclassification rate and lower overall usefulness of the model. These tradeoffs are key drivers in the thesis.

Just as important as understanding tradeoffs and model performance metrics is the comprehension of the implications of adding new variables. Throughout the thesis, our desire to improve the model and deliver better results tempts us to include data that marginally improve performance. Although it is possible to improve overall misclassification by adding some extra variables, we avoid this. We find that adding variables without very high explanatory power adds complexity, reduces robustness, and can lead to overfitting.

Despite all the possible extensions of this research, our findings present valuable insights to Coyote Logistics. The thorough modeling process validates much of the intuition from the experts. Data-backed decisions enable firms to have greater success and gain competitive advantage. This research represents a step in the right direction for Coyote in investigating predictive analytics for their operations. The model, developed using six explanatory variables with statistical significance, results in a 76.4% resource reduction while incurring an impactful error of 2.4%.

Figure 3. Confusion Matrix Results Comparison for Validation and Customer Test Data

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Reducing Shipment Variability through Lean Leveling

By: Melissa Botero Aristizabal and Fabian Brenninkmeijer
Thesis Advisor: James B. Rice, Jr.

Summary: This research focused on reducing shipment variability between manufacturer warehouse and customer distribution center. We used the leveling principle as defined by lean theory to create predetermined customer shipments for the top selling SKUs. We determined the optimal degree of lean leveling implementation through simulation analysis of various order policies. Sending frequent, small, recurring shipments on a weekly basis could lead to improvements in service level, transportation cost and cash.

Introduction
Supply chain professionals are often confronted with the increasingly difficult task of meeting service promises while operating with high variability in order patterns. This volatility leads to supply chain-wide inefficiencies, high operational complexity, low service levels and substantial costs. These challenges are particularly prevalent among companies operating in the consumer goods industry due to the vast numbers of ever changing SKUs and the frequent use of promotions. Weeks of consistently over ordering certain items are often followed by periods of close to zero orders of the same item. Our research focused on applying the lean leveling principle as a measure to counteract the challenges posed by oscillating order placement.

The current highly volatile order system poses key challenges to the sponsor company. The company often has to pay a premium freight rates to fulfill service level promises. Furthermore, both buyers and sellers hold higher levels of inventory as a contingency plan to buffer against unpredictable peaks in demand. The motivation for this research was to achieve a more uniform flow of goods and thereby addressing the root cause instead of curing symptoms.

Leveling distribution can make the shipping process more predictable and therefore easier to manage. Whereas lean concepts have been applied extensively to the manufacturing domain, lean application in distribution

KEY INSIGHTS
1. Managing shipment variability is a key challenge for supply chain professionals. While reducing variation across the supply chain has limits, each minor advancement effort could yield improvements reflected in the company profitability and customer satisfaction.
2. Lean principles have been applied extensively in manufacturing settings, while the logistics domain remains a relatively unexplored lean frontier.
3. Lean leveling aims to reduce variability through the more frequent production of top selling SKUs. Applying the lean leveling principle to distribution can improve service level, transportation cost and cash (working capital tied up in inventory).
processes has received relatively little attention in practice. We simulated various order policies based on lean leveling principles with the goal of improving operational performance across supply chain echelons.

Creating a new Order Policy
The research focused on diminishing the impacts of variability by creating more stable inventory flows between a supplier warehouse and a retailer’s distribution center. Figure 1 depicts the degree of shipment variability experienced by a typical customer of the sponsor company under the current order system. The range of 5 to 22 weekly shipments confirmed the need to address the issue of volatility.

We developed a model based on one year of historical demand, supply and forecast data. We created a new order policy based on the following 3 key steps: SKU segmentation, simulation, evaluation.

1. SKU segmentation
We utilized lean theory to develop a new order policy with the goal of smoothening out demand volatility. Under lean theory, a daily fixed production plan is applied for the top 50% of SKUs. The daily manufacturing of the same products allows the manufacturing team to develop experience on the process, standardize it and improve it, something known as “Economies of repetition.”
Following the lean leveling principle derived from the manufacturing domain, we conducted a SKU segmentation to identify the top selling 50% of SKUs. The resulting top SKUs were used to find the base quantity by SKU to be shipped continuously under the new policy.

2. Simulation
We built a model to simulate the effects of the new order policy based on varying degrees of lean implementation, in order to determine its viability. The simulation determined the number of cases ordered by week, inventory levels, and anticipated lost sales by week and by SKU.

The new policy consisted of two components: a fixed part and a variable part. The fixed part was comprised of a percentage of the base quantity derived from the segmentation analysis. The variable component follows the process logic of the sponsor company, taking into account current inventory levels, demand forecasts and promotional data. Figure 2 shows the reduction in weekly shipment variability under the new order policy. In this figure, the adjustable fixed order percentage was set at the default rate of 50% of the average.
Under the new policy, the fixed order component represents a consistent minimum shipment level which enables the overall reduction in volatility. At the same time, the variable order component gives the company the flexibility to cover sudden demand peaks.

3. Evaluation

The results of the simulation runs were compared with the actual performance of the sponsor company according to the following criteria: cash (inventory levels), transportation cost and service level. An improved inventory policy should be based on an approach that balances the three criteria. This enables sustained gains for both buyers and sellers across the supply chain.

To obtain the optimal inventory order policy, we conducted a sensitivity analysis based on the adjustable percentage of fixed versus variable shipments. Figure 3 shows the impact of the fixed order percentage on the three evaluation criteria.

The more fixed shipments a company has, the more shipments can be planned in advance, which reduces the probability of having to pay for premium freight rates. Therefore, the transportation cost decrease as the fixed percentage of the average increases. Under the new order policy with fixed recurring shipments, the sponsor company can rely on the same carrier and even the same drivers, which will create efficiencies out of habit. Overall, the probability of a shipment arriving on time increases with a higher rate of fixed shipments.

More frequent deliveries reduce inventory requirements at the customer warehouse. However, inventory levels become increasingly inflated with a rising fixed percentage because available quantities start to exceed demand levels more often.

Since all three evaluation criteria had to at least remain the same under the new policy, the team established a feasible region with potential order policies. At a fixed order percentage of 75% the three evaluation criteria were equally balanced between buyer and seller.

Conclusions

Shipping variability affects the performance of every global supply chain. Causes such as changing customer behaviors, lack of coordination between supply chain partners, and disruptions prevent companies from achieving a more uniform flow of goods. We demonstrated that lean leveling
could effectively reduce shipment variability while leading to improvements of service levels, transportation costs and cash requirements.

Operating with the lowest possible shipping variability does not necessarily lead to the best results due to the highly volatile nature of the consumer goods industry. Instead, reducing shipment variability should be seen as a means to the end of improving cash requirements, transportation cost, and service level. For an optimal strategy, companies should find a balance of fixed and variable shipments of the top selling SKUs. Companies should further balance the evaluation criteria to potentially enable sustainable gains for both buyers and sellers. Sending frequent, small, recurring shipments of the Top SKUs on a weekly basis could lead to better operational performance than infrequent bulk shipments of the same items.

A careful analysis of the order policies should be conducted with the goal of determining the optimal degree to which lean leveling should be applied. An order policy, combining the synergies gained from lean leveling while maintaining the flexibility to respond to unusual demand volatility, could lead to a win-win situation in the long run.

**Conclusion**

The AHP provides ShopCo a tool to prioritize inbound loads awaiting shipment by assigning priority scores to each load based on factors defined by ShopCo.

ShopCo will be able to identify the relative priority of the loads and determine which loads should receive priority when carrier capacity is constrained, facilitating improved service levels without incurring additional costs. Further, the Knapsack optimization model found opportunities to improve the load priority shipped by up to 8.3% as compared to the current load assignment.

We believe this research will benefit not only ShopCo but also other companies and industries managing their inbound transportation with carrier capacity constraints by applying this framework. Although the factors and sub-factors used may differ, this underlying framework can align load priority with company objectives.

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**Figure 3: Sensitivity Analysis of adjustable fixed order percentage**

![Sensitivity Analysis: KPI Change](image-url)

- **Transportation Cost**
- **Service Level On Time**
- **Service Level Case Fill Rate**
- **Inventory Value Customer DC**

The graph shows the sensitivity analysis of KPI change with respect to the fixed percentage of average demand.
Preemptive Solutions to Reducing Call Center Wait Times

By: Qiao Chu and Nisha Palvia
Thesis Advisor: James B. Rice

Topic Areas: Queuing Theory in Call Centers, Simulation, Segmentation, Home Security Industry

Summary: The security alarms services market in the United States delivers hardware equipment and services to homeowners and businesses to help monitor and enhance personal property protection. For this thesis, MIT partnered with OnProcess Technology, a managed services provider specializing in complex, global service supply chain operations. Together, the team developed a robust framework to preemptively reduce the number of inbound customer calls, and thereby improve customer service. The team followed a three-step process to develop this framework: customer segmentation, call center queue simulation (using interarrival times, service times, and number of agents), and preemptive solution development.

Qiao graduated with a Bachelor of Engineering degree in Electrical and Computer Engineering from University of Toronto. Before coming to MIT, she worked as a technology consultant with Citrix for 3 years.

Before coming to MIT, Nisha Palvia graduated with a Master’s in Business Administration from IE Business School in Madrid. She worked as an analytics consultant with A.T. Kearney for 4 years and will be rejoining the firm following the MIT SCM program.

KEY INSIGHTS
1. Security companies fail to utilize preemptive solutions when managing inbound customer calls and default to reactive measures, which unnecessarily increase wait times and queue lengths.
2. Customer segmentation can create targeted solutions for prominent customers, based on call volume, reason for call, and sales.
3. A small percentage of call avoidance can have a large impact on queuing performance indicators such as queue length, wait time, and overall customer satisfaction.

Introduction
The security alarms service market has seen significant growth in the last twenty years with the growing prevalence of cybersecurity and remote monitoring as well as a rapidly growing middle class segment of the US population. In fact, the home alarm securities and automation market is expected to triple by 2018. Many security alarm services companies have not realized the promise of waves of new technologies that are creating breakthroughs in the sector of inbound service queue management. Some of these major developments include the transition from voice based service to automated web services and the transition from live phone call issue resolutions to intelligent voice recognition.

Players in the security service market try to maximize customer satisfaction by creating highly efficient and high performing call centers. Typical benchmarks used to assess this performance include service level, average speed to answer, call duration, first call resolution rate and abandoned rate. Agents track these variables in dashboards that are highly advanced and have innovative reporting mechanisms including weekly metrics reports, labor attrition reports, schedule adherence reports, agent ranking reports, and call resolution reports.

For the purposes of this thesis, we have teamed up with OnProcess Technology (OPT) to provide a planning framework that utilizes these breakthroughs to allow our client company, AlarmCo, a major security service provider, to shift from inbound service queues to preemptive next issue avoidance using queuing theory and predictive analytics. Developing preemptive measures in place of reactive solutions could cut queue length, reduce average wait times, and free up agent capacity.
To understand the current call center system, the MIT thesis team simulated the queue of an AlarmCo call center by calculating interarrival rates, service time, and using the number of agents by hour and day of week. The call center as a queuing system can be mapped as per Figure 1.

The team also strategically segmented the AlarmCo customer base and developed targeted preemptive solutions for prevalent segments. After adjusting the queuing inputs per the potential preemptive solutions, we were able to directly assess the quantifiable impact of introducing preemptive solutions to this industry.

**Analysis, Methodology, and Insights**

**Analysis**
The team first requested three separate sets of data including details on inbound customer calls, customer demographics and labor resource plans. We then performed preliminary data analysis to understand the top customer reason codes and solutions for the inbound traffic. Analysis of call volume reveals that 80% of calls are made by customers with seven of the thirty possible issue codes.

Taking a closer look at these top issue codes, we found that a majority of calls were warm transfers to sales (agent transfers call, without concrete solution), solutions that were accepted by the customer, and resolved solutions to general questions. The call data also revealed that Sunday, Saturday, and Friday had the lowest call volumes while the days with the largest number of incoming calls were Monday, Tuesday and Wednesday. Additionally, we noticed a dip in total call density in the months of December and July. When studying the distribution of calls, we learned that the highest call count on any Sunday for the calendar year was 1500, nearly 40% lower than the maximum number of inbound calls on Monday.

**Customer Segmentation**
Next, customers were segmented by demographic groups and prevalence of top reason codes (Figure 2). Demographic data helped us group AlarmCo customers into two categories: business clients and homeowner clients. Homeowners account for 81% of sales while the business clients account for the remaining 19%. The homeowner category can be further broken down to platinum or premium customers accounting for 15% of...
customers, silver customers (average package holders) accounting for 58% of customers and finally, basic package holders, accounting for the remaining 27%. The team segmented the homeowner customers into 18 sub groups based on their age, income, and English proficiency level.

Queuing Simulation
The team selected the appropriate queuing model based on the inbound call center data and decided to approximate the interarrival rate and service rate as a Poisson distribution. In order to make sure the selected model, $M/M/n$, was representative of the call center, the team extracted empirical inputs (interarrival rate, service rate, and the number of agents) and outputs (average wait time and average queue length) from the customer queue data, and compared the theoretical outputs with the empirical data. Since the difference fell within a 10% validity threshold, it could be concluded that the $M/M/n$ model accurately emulates AlarmCo’s inbound customer call queue.

Preemptive Solutions
Customer segmentation led to the development of different preemptive solutions addressing major call reasons codes.

We developed 20 solutions that fell into five categories:
- Automated Remote Services
- Education
- Online Resources
- Telephonic Assistance
- Proactive Analysis

We calculated the impact of the recommended preemptive solutions on the number of inbound calls using a feasibility and risk ranking.

Comparative Analysis
After calculating different success rates for each of the twenty preemptive solutions, we applied a weighted average percent reduction of interarrival rate for each day and hour. With these new and improved interarrival rates, the team was able to rerun the queuing simulation and compare three different scenarios: implementing no preemptive solutions (as-is state), implementing the most favorable (twelve) preemptive solutions, and finally, implementing all twenty solutions (cherry pick). After updating the queuing model interarrival rates, we see that wait times steadily decrease with implementation of each scenario. If AlarmCo conservatively moves forward with twelve of the twenty solutions, average wait times reduce
from 6.88 seconds to 4.47 seconds in the morning, 7.74 seconds to 5.03 seconds in the afternoon, and 8.84 seconds to 5.74 seconds in the evening. If the client implements all twenty solutions per the cherry pick scenario (best case), average wait times reduce from 6.88 seconds to 4.03 seconds in the morning, 7.74 seconds to 4.53 seconds in the afternoon, and 8.84 seconds to 5.17 seconds in the evening (Figure 3).

Conclusion

Three major insights can be drawn from the process of applying queuing theory in this research:

- Poisson distribution is a robust model for a general queuing model
- Small changes in the number of inbound calls can have a large effect on the queue
- Tradeoffs have to be made between the service level and resources

While the home security industry in the United States has seen vast change in the last decade in terms of technological innovation, security companies are still not able to fully utilize call center data to develop proactive solutions in place of reactive measures. In closing this gap, the team addressed the following question for AlarmCo: “How can we improve the customer service experience for customers of a major security service provider in the US?” By analyzing the outputs of the simulation before and after adjusting the dataset, the team quantified the impact of preemptive solutions on the call center queue. Ultimately, narrowing to twelve strategic preemptive solutions led to the enhancement of the as-is queuing model, reducing average wait time by up to ~35%. Our chosen hybrid model is a conservative and feasible approach in implementing preemptive solutions with the goal of minimizing inbound calls and reducing average wait time. The twelve solutions, scattered across all five preemptive solution categories, have strong support from stakeholders and according to our research, will work successfully with other similar players in the home alarm securities market.
Production Planning with Complex Cost Drivers

By: Ian Chua and Thomas Heyward
Thesis Advisor: Josue Velazquez-Martinez

Topic Areas: Supply Chain Planning, Optimization

Summary: This thesis provides a new lot sizing model formulation for manufacturing firms that contract third party logistics (3PL) provider’s warehouses. The formulation extends existing models to account for the change in inventory holding costs depending on 3PL warehouse utilization. In addition, it provides a novel method for considering multi-tiered setup costs for products that share common setups. The new formulation produces production plans that reduce relevant supply chain costs for firms with these features.

Introduction

Many manufacturers have to strategize around seasonality and capacity constraints when planning production schedules. Companies need to come up with production schedules that consider demand, inventories, production capacities, and when to use 3PL services. Typical production strategies prioritize maximizing line efficiency which favors large lot sizes and few setups. On the other hand, logistics strategies prioritize minimizing inventory costs which favors smaller lot sizes and more setups. Lot sizing problem formulations provide a means for considering both setup and inventory costs to achieve the optimum balance.

Niagara Bottling Co (Niagara) sponsored thesis research with MIT to improve their production planning process. Niagara wanted a method that explicitly considered the cost impact that production lot sizing decisions have on utilization of 3PL warehouse space.

KEY INSIGHTS

1. Manual planning processes are time consuming and limited in the number of cost drivers that can be focused on.
2. Implementation of lot sizing problems requires the right formulation that fits the business environment.
3. Production lot sizing optimization is not always a trade-off between setups and inventory. In some cases, improvements can be made in both areas simultaneously.
Operational Context
Niagara operates with a complex network of production facilities. Each plant has multiple production lines capable of producing a variety of products. The products produced on a line can have shared attributes of bottle size and package size. Switching between products that do not share these attributes constitute a longer changeover time than switching between products that do.

Niagara demand has seasonality with peak demand exceeding production capacity during certain periods of the year. Niagara prepares for the peak season by building inventory during periods with excess capacity. The inventory needed for peak seasons are stored in 3PL warehouses.

Niagara plants have some limited inventory warehousing capacity. The plant warehousing cost structure is significantly lower than the cost structure for the 3PL warehouse. Additionally, there are transfer costs associated with transporting and handling of inventory entering the 3PL warehouse. Niagara expects that because of this cost structure, transfers to the 3PL warehouse should only occur during periods where inventory is being built for the peak season.

Instead, Niagara has observed that even during peak periods, inventory is being transferred to the 3PL warehouse as shown in the Figure 1. This behavior is attributed to large lot sizes that maintain high utilization of the machines, but are incurring increased inventory holding costs. Hence this thesis focuses on explicitly incorporating 3PL holding costs into Niagara’s production planning process.

Capacitated Lot Sizing Problems
Given the specific features of Niagara’s business, we developed a formulation based on the Capacitated Lot Sizing Problem (CLSP). The basic CLSP formulation accounts for the capacity limitations and seasonal demand changes faced by Niagara. The different production features of each line are incorporated using an existing extension in the literature for multiple machines.

However, certain aspects of Niagara’s business could not be modeled using the existing formulations. A new extension for the formulation was devised to address these features. Additional variables were introduced to track the amount of inventory in 3PL warehouses and when an inbound shipment occurred. Other variables were added to track the changeover of major setups for bottle sizes or packaging separate from minor setups for labels.

Adding these features to the model provided the necessary integrated framework for assessing tradeoffs between production and logistics cost considerations.
Implementation
The model formulation was implemented using Gurobi optimization and Python software. These tools allowed the model to find a solution when considering the myriad products and machines in Niagara’s network. The model has the flexibility to span the planning process from strategic to operational. For the purposes of this thesis, we focused on tactical planning using a weekly time period and aggregated product demand at a bottle-package level. This presented the greatest opportunity for Niagara since tactical planning is relatively less developed.

Setup costs were derived as the opportunity cost of not producing bottles while the machine is down during the changeover. Holding costs were calculated using annual warehouse costs including labor, insurance, rent, and tax. The annual costs were converted into a weekly cost per footprint of storage.

A representative subset of Niagara’s national network of plants and 3PL warehouses was used to validate the functionality of the model. This representative region included twelve production lines across three plants capable of producing 90% of Niagara’s products. The region also includes a central 3PL warehouse for extra inventory storage.

Some comparison with actual production data was made, however, its utility as a benchmark is limited. Production data reflects daily plans on an SKU level whereas planning results are aggregated. In addition, the model used the actual demand data for the entire time horizon, which was not available at the time production decisions were made. Therefore, an additional benchmark was performed comparing the model results to a manual plan developed using current practices at Niagara.

Sensitivity analysis was performed to assess the robustness of the model to changes in the relative holding and setup costs. The holding and setup costs were increased by a factor of two and four independently. The resulting number of setups and amount of inventory held were compared to assess the impact these changes had on the plan.

Figure 2: Transfer inventory from plant to 3PL to lower costs
Results

The representative region benchmark demonstrated the full functionality of the model. The results showed a 33% reduction in setup and inventory costs compared to the actual production data. Although the cost comparison is suspect for the reasons already stated, the model results do reveal a possible way to reduce inventory costs. The actual inventory data showed that the plant warehouse was underutilized while there was still significant inventory in the 3PL warehouse. The model moved this inventory into the plant to reduce holding costs as shown in Figure 2. Although there are some costs not considered by the model in executing this strategy, it represents cost savings worth further exploration by the company.

The benchmark against the existing planning process is more informative on cost comparison. The model formulation showed a 22% reduction in setups, a 9% reduction in inventory, and a 74% reduction in transfer events. The findings are remarkable in that both setups and inventory were reduced. The model reduces setups by increasing inventory of slow moving products. This increase in inventory is offset by reduced lot sizes for the fast moving products. This shows the cumulative demand for fast and slow movers and the cumulative production for the manual plan and the model. It’s clear that the manual plan cumulative production for fast movers exceeds demand, which increases inventory. Whereas the model is able to build less than cumulative demand by drawing down existing inventory.

The reduction in transfer events is significant. This is likely a function of the limits of a manual planning process. Visualizing the trade-off between setups and inventory is straightforward. However, understanding which items are best to hold at the 3PL warehouse to reduce costs is more complex and time consuming.

The sensitivity analysis showed a +/-6% change in setups for a corresponding 300% increase in setup cost or holding cost. The inventory increase under these conditions was 174%, but only increased the average plant warehouse utilization from 3.4% to 9.4%. These results indicate that the model is relatively robust to inaccuracies in input costs.

Conclusions:
The implementation of a lot sizing model allows more complex cost considerations to be accounted for in the planning process. This improves cost performance while also reducing the effort required for planning. Capturing cost savings by business process improvements like this are compelling. A company can reduce their costs with little investment because the improvement comes from better utilization of their existing assets.

Figure 3: Cumulative Production relative to Demand
Intermodal Variability and Optimal Mode Selection

By: Tianshu Huang and Bernarda Serrano  
Thesis Advisors: Dr. Chris Caplice & Dr. Francisco Jauffred

Topic Areas: Transportation, Mode Choice, Inventory

Summary: This research focused on incorporating the transit time variability into the transportation mode selection process. We identified a probability distribution for the transit time per unit of distance to quantify the impact of transit time uncertainty on inventory cost. Then, we built a model that calculates the total logistics costs and compares the results for two transportation modes: intermodal and truckload. Results show that a particular lane is more likely to be assigned to truckload for high load values and/or high service levels.

Before coming to MIT, Tianshu worked at Weston Foods and Unilever for various roles related to logistics. He holds a Master’s in Operations Research and a Bachelor’s in Engineering Science, both from the University of Toronto.

Before coming to MIT, Bernarda worked as a Supply Planner for a company in the consumer goods industry. She holds a Bachelor’s degree in International Business from Tecnologico de Monterrey.

KEY INSIGHTS

1. Retailers often select the transportation mode based on the carrier’s rate and the expected transit time. However, they should also consider the impact of transit time variability on logistics cost.

2. To quantify the impact of transit time variability, a probability distribution can be used. For the dataset used in this analysis, results show that Normal and Lognormal distributions model the transit time in a very similar way.

3. The sensitivity analysis shows that an increase in load value or service level makes truckload more favorable than intermodal.

Introduction

Transportation cost is one of the major drivers of logistics costs in any retailer’s supply chain. Since it is dependent on the mode of transportation, optimizing mode selection is imperative to minimize costs. Different transportation modes and different carriers within a mode offer varying rates, lead times and service level.

The traditional approach to the mode selection process is to choose the carrier that offers the lowest rate or the shortest delivery time. However, each mode also has an associated transit variability that impacts the total logistics cost.

Given this uncertainty, retailers need to increase the safety stock in distribution centers to maintain a high service level, resulting in higher inventory holding costs.

Our research sought to incorporate additional variables, such as lead time uncertainty and service level into the mode selection process. We developed a model that calculates the total logistic cost incurred by the company for two transportation options: over the road truckload (TL) and intermodal (IM).

Our sponsor company, ABC Stores, uses a mix of truckload and intermodal to move goods from vendor facilities to distribution and mixing centers. The company assigns most of the shipments to truckload, but they believe that there is a cost savings opportunity by switching some of the lanes from truckload to intermodal. Therefore, ABC Stores was interested in knowing what the tradeoff between costs, lead time, transit variability and service levels is for each mode choice.

Transit Time Distribution

Because this study focuses on quantifying the impact of transit time variability, finding the most appropriate probability distribution to model transit time was critical. We used data of shipments between October 2015 and
November 2016 to find the best distribution of Time/Distance (in hours per mile) for each mode.

As shown in Figures 1 and 2, both truckload and intermodal have right-skewed transit time distributions. The goodness-of-fit results show that the Normal and Lognormal distribution fit the data well. The probability that the data do not follow the Normal or Lognormal distributions for Truckload is less than 1%. For Intermodal, the probability that the data do not follow a normal distribution is less than 1%, and the probability it does not follow a lognormal distribution is less than 4%. Neither number is statistically significant. Therefore, both distributions were used for modeling the transit time.

**Required Time/Distance**
The required Time/Distance is expressed in our model as $(\mu, \sigma, \text{service level})$. It is measured in hours per mile. It represents the transit time over one unit of distance given a certain mean $(\mu)$, a standard deviation $(\sigma)$, and a specific service level. The service level refers to the percentage of time that an order is delivered on time.

For a normal distribution, the $t(\mu, \sigma, \text{service level})$ can be found using the standard normal table. For other distributions, it can be found by calculating the area under the distribution curve that covers the required service level.

For example, in Figure 3, the transit time does not follow a normal distribution. The required time/distance can be found by finding the point in the $x$-axis that covers 95% of the total area under the curve.
Total Cost Equation
The total cost includes two components: transportation cost and inventory cost.

\[
\text{Total Cost} = \left[ \text{Transportation Cost} \right] + \left[ \frac{h}{8760} \times C \times D \times t(\mu, \sigma, \text{service level}) \right] \]

Where:
- CPL = Carrier cost per load ($/l).
- D = Annual demand of the lane in number of loads (l).
- \( h/8760 \) = Inventory holding rate ($/$/h).
- C = Value of the load ($/l).
- d = Distance (mi.).
- t(\mu, \sigma, \text{service level}) = Time/Distance for a given service level (h/mi.).

1) The transportation cost is a function of the carrier’s cost and the volume of the lane. This rate is provided by carriers and varies between lanes. It considers not only the distance between the origin and destination points but also geographic factors that could impact the transportation mode performance. The rate is also dependent on the volume of demand.

2) The inventory cost is determined by the level of safety stock (SS) that the company should maintain in order to protect against transit time uncertainty. The safety stock is a function of the demand during the transit time plus a buffer to cover for the transit variability. The transit time and its variability are given by the distance and the parameters we set for the Time/Distance probability distribution. To calculate the cost of the safety stock we included the monetary value of a load and the inventory holding rate defined by the company.

Discussion
ABC Stores’ dataset contains 1662 different transportation lanes. Of these 1662 lanes, ABC Stores uses truckload more frequently for 64% of the lanes, intermodal more frequently for 35%, and uses both modes with the same frequency for less than 1% of lanes (13 lanes). This last set of lanes was excluded from the analysis.

Having constructed the total cost equation, we applied the model to ABC Stores’ dataset to generate transportation mode recommendation for 1649 lanes. For this initial comparison, we used the actual demand of each lane provided in the dataset. For the load value, we assumed an average of $25,000.

Our model’s recommendation coincides with ABC Stores’ mode choice on about 74% of the lanes. For 4% of the lanes, our model recommends intermodal while the company uses truckload. Twenty-one percent of lanes were assigned to truckload by our model while ABC Stores uses intermodal. These results show that the total cost equation recommends truckload more often than what ABC Stores selects.

Figure 44: Sensitivity Analysis based on Load Value
Sensitivity Analysis
To investigate the impact of different load values on mode selection, a wide range of load values, from $1,000 to $120,000 were used to compute the total cost using the total cost equation. Values ranging from 1 to 100 were used to evaluate how changes in the volume affect the percentage of lanes assigned to each transportation mode. We also measured the dynamics of mode selection changes with respect to service levels from 0 to 100%.

These sensitivity analyses show that:
• The variation in the model's recommendation when using parameters of the Normal vs. Lognormal distribution is insignificant, as can be seen in Figure 4. The horizontal axis represents the load value measured in dollars per load and the vertical axis represents the percentage of lanes assigned to a specific mode. The blue (TL(ND)) and gray (TL(LnD)) lines represent the percentage of lanes assigned to truckload using normal and lognormal distribution, respectively. The orange (IM(ND)) and yellow (IM(LnD)) lines represent the percentage of lanes assigned to intermodal using normal and lognormal distribution, respectively.
• An increase in the load value would enlarge the difference in inventory cost, increasing truckload’s cost advantage.
• As the volume increases between 0 and 20 loads per year, the percentage of lanes assigned to Intermodal increases.
• The percentage of lanes assigned to truckload increases as the service level increases.

Conclusion
We investigated how to optimize the transportation mode selection process for ABC Stores. We developed a total cost equation that integrates transportation costs and transit time variability in terms of inventory costs. The main findings of this study show that:
• The average and standard deviation of transit time are impacted by distance. The relationship between average transit time and distance is non-linear as there are many other factors such as driving hour limitation, pick up delay, etc. that are also relevant to transit time.
• The expected transit time of truckload is shorter than the expected transit time of intermodal (lower mean).
• For this particular dataset, the model generally favors Truckload over intermodal because the lower average and standard deviation result in lower inventory costs. Therefore, most of the lanes are assigned to truckload.
Serialization of Prescription Drugs in the US: A Centralized View

By: Aisha Nabiyeva and David Z.Y. Wu
Thesis Advisor: Bruce Artzen

Topic Areas: Distribution, Healthcare, Tracking & Tracing

Summary: The 2013 Drug Supply Chain Security Act (DSCSA) of 2013 requires serialization of prescription drugs across the whole pharmaceutical supply chain. This thesis assesses the costs associated with serialization implementation on manufacturers and distributors/retailers. Taking the perspective of a centralized data model, we tested the feasibility of implementing a centralized database under both data nesting and unit level relational models. The findings suggest that serialization using a centralized data model would in all cases incur a higher proportional cost than using a decentralized model.

Introduction
The pharmaceutical industry currently faces the challenge of readying themselves for serialization of all prescription drugs. With the first phase slated for completion in Fall of 2017, this topic is top-of-mind for many industry players. This thesis explores the impact of the Drug Supply Chain Security Act (DSCSA) on various stakeholders in the pharmaceutical supply chain. Specific attention has been dedicated to the impact on manufacturers and distributors/retailers. This thesis tests the feasibility of implementing a centralized database under both data nesting and unit level relational models. This is in contrast to the decentralized system, which is further explored in the partner thesis by Chang and Mohan, Impact of Drug Supply Chain Security Act on US Pharmaceutical Industry Under Decentralized Information Flow.

Both quantitative and qualitative analysis are employed in this thesis. Quantitative modeling of supply chain costs was conducted using publicly available industry data. Qualitative analysis consisted of stakeholder interviews, process mapping, and time studies to determine the extent of process changes and what they should look like to conform to DSCSA.

After accounting for the current state of implementation, as well as real-world constraints, the findings indicate that the best-practice scenario to conform to DSCSA is to use a Centralized data management and data nesting model. Although this option is estimated to be 67% costlier than the least expensive scenario, it offers a more robust and secure system that allows for better long-term scalability.

Methodology
The analysis of the impact of DSCSA and serialization on the pharmaceuticals supply chain was carried out by modeling...
the financial and inventory impacts in a hypothetical network. Information gathered during the interview process indicated that, in order to measure the costs and advantages of each possible serialization model, estimates for each cost factor needed to be drawn up. These cost factors were determined to be: Ongoing Operational Costs, IT Investment Costs, and Capital Expenditures. Each of these cost factors were individually estimated using a top-down methodology, using industry data available through public sources, and validated for directional accuracy using a bottom-up analyses with the thesis sponsors.

Eight distinct scenarios were determined based on a combination of the data model and the relational model. Within the data model, four possible options were available: Centralized – Manufacturer lead, Centralized – 3rd Party lead, Centralized – Government lead, and Decentralized. Within the relational model, two options existed: either Unit Level tracing, or Nested Data tracing. The Nested Data model is also referred to as the “inference” model where individual product units are serialized and grouped together in a serialized outer box. This allows the outer box serial number to link to all the inner individual serialized products, reducing the steps needed by eliminating the need to scan each individual product. A combination of the data and relational model options result in the eight distinct scenarios mentioned. The full tables for each scenario is provided in Figure 1.

Cost Categories
To assess total cost impact from Serialization the following costs are considered:

- Ongoing Operational Costs
- One Time Capex Costs
- IT Investment Costs Recurring and One Time

Ongoing Operational Cost
Ongoing Operational Costs was estimated based on the assumption that Serialization using the Nested Data relational model would require additional labor and equipment maintenance to implement effectively. This approach modeled the time necessary to complete each step of the packing, shipping and receiving process, and then estimates the total costs. Information was collected on the number of individual cases required, and the number of cases per pallet, as well as the steps required at each stage in the process. Average time per task was obtained through interviews with industry stakeholders. An industry average labor cost rate was then used to convert the total time required to a cost figure. The formula below illustrates the Operational Cost calculation method:

\[
\text{Operational Costs} = \text{Minutes per task} \times \text{Annual Volume} \times \text{Hourly labor rate}
\]

Figure 1 - One-Time Capex Costs Structure
One Time Capex Costs

Capital Expenditures differed significantly depending on the serialization scenario. In this case, the cost difference is driven by the distinction between a Nested Data relational model vs a Unit Level relational model. In a Nested Data model, the capital expenditures are expected to be higher due to the added complexity of data aggregation. In a Unit Level model, some of the capital equipment would not be necessary. In each case, production volume was used to determine the quantity of equipment needed to obtain sufficient serialization capacity. Published equipment prices were then used to determine the total investment cost. To estimate the industry wide initial capital requirements we have constructed the tree of all applicable costs. These costs relate to:

- Line upgrade for serialization,
- Additional inbound equipment,
- Additional outbound equipment.

The Nested Data approach only applies to Manufacturer and Wholesaler levels, since the upstream supply chain is assumed to all be comprised of unit-level transactions.

IT Investment Costs

IT Investment Cost is calculated using a combination of the investment necessary in storage space, as well as the cost of setting up the data interfaces between partners in the supply chain. Storage space investments include the capital expenditures on physical assets (servers and racks), as well as the cost of cloud storage if managed by a 3rd party. The cost of setting up data interfaces includes all the IT implementation costs associated with integrating the serialization database with the existing IT architecture. This portion includes both a one-time cost, as well as an ongoing annual cost.

The IT costs have been calculated based on the number of storage requirements and transactions required per each echelon. It also considers that at each point of transaction all the information will be provided by the receiver of the product.

\[
\text{IT Investment One-time Cost} = \\
\left(\frac{\text{Annual Production Volume} \times \text{Data Storage needed}}{\text{Storage Capacity per server}}\right) + \\
\left(\text{Number of downstream supply chain partners} \times \text{Cost per database linkage}\right)
\]

\[
\text{IT Investment Recurring Cost} = \\
(\text{Annual maintenance hours needed} \times \text{Labor cost per hour})
\]

Figure 2 - Investment Costs Calculation
Comparison of Centralized and Decentralized, Nested Data vs Unit Level Scenarios

All the costs above are calculated based on a number of assumptions. The assumptions and the dynamics of the industry complicate the precise calculation of the financial impact of serialization on the whole supply chain. For this reason, relative comparison of the scenarios is introduced (Figure 3).

Further limitations and areas for future research are explored in the conclusion sections of the thesis.
Balancing Product Flow and Synchronizing Transportation

By: Priya Andleigh and Jeffrey S Bullock
Thesis Advisor: Dr. Ahmad Hemmati and Dr. Chris Caplice

Topic Areas: Optimization, Supply Chain Planning, Transportation

Summary: Traditionally, production and transportation planning processes are managed separately in organizations. In such arrangements, order processing, load planning, and transportation scheduling are often done sequentially, which can be time consuming. Establishing a proactive steady flow of products between two nodes of a supply chain can bypass this order-plan-ship process. A steady flow of products can reduce transportation costs, increase cross-dock productivity, and reduce bullwhip effect upstream in the supply chain. This thesis develops an analytical framework to calculate this steady flow. The methodology developed in the research also presents the opportunity for new and innovative contract types with transportation providers.

Introduction

Products flow through any shipper’s network based on customer demand. For a given product, that demand typically fluctuates over time. Many Stock Keeping Units (SKUs) may be fast-moving and always have demand, whereas other SKUs may have more sporadic demand cycles. When a product’s demand is higher, and more frequent, that product is shipped consistently. Most commonly, shipment of products from the plant to the warehouse entails three activities: order, plan, and ship. The warehouse places an order to the plant for products in accordance with actual customer orders as well as forecasted demand. The placing of an order triggers the load planning or load building process that entails deciding which SKUs should be placed on a single truck constrained by weight and volume limitations. After load planning is completed, the shipment process begins. Transportation carriers are then contacted to request for required capacity. Upon acceptance of the load by a carrier, load pick-up planning is done. Subsequently, the load is picked up and transported to the warehouse.

Instead of waiting for orders to be placed, would it be beneficial to ship a certain amount of the expected demand for that product proactively? Both financial benefits and risks are associated with setting up this type of distribution structure. The focus of this thesis is to provide an analytical framework to maximize the benefits while minimizing the risks. Some benefits include shorter lead-times, decreased transportation costs, and warehouse cross-docking. The major risk is the potential to increase inventories and consequently the inventory holding costs. To take advantage of the savings while managing the risks, the framework determines which SKUs are eligible and how much of each SKU should be shipped proactively.

KEY INSIGHTS

1. The traditionally independent production and transportation planning processes can lead to excessive lead times and added variability in the supply chain.
2. Despite variable demand, a steady flow can be viable for many SKUs with a variety of characteristics.
3. Having a steady flow of products can yield major benefits in transportation and cross-dock savings.

Prior to MIT, Priya Andleigh worked as a Supply Chain Business Consultant with a process optimization software provider, Aspen Technology. She received her Bachelor of Engineering from Nanyang Technological University, Singapore.

Prior to MIT, Jeff Bullock worked as a Senior Transportation Analyst at Ryder System, Inc. He received his Bachelor of Science at Brigham Young University in Manufacturing Engineering Technology.
Methodology

The focus of this study is a plant-to-warehouse lane. To determine the optimal steady flow on the plant-to-warehouse lane, the demand data from the warehouse out to the customers was utilized. This data was aggregated to a weekly level, and the unit of measure for time used in this model was a week. The overall approach that was developed to determine the steady flow is shown in Figure 1.

The process is as follows. Starting in boxes 1 & 2 (Figure 1), SKU level forecast and historical data are used to characterize the demand. First, descriptive statistics (box 3) of the demand are calculated. In order to do this, a determination needs to be made as to how much data would be used for these calculations.

In other words, how many weeks of historical data (say, H weeks) and forecast data (say, F weeks) should be used? The number of weeks for each are input parameters that can be tuned. The calculated statistics from the specified time frame (H weeks + F weeks, henceforth called “model horizon”) include mean of demand, standard deviation of demand, coefficient of variation (COV) of demand, minimum demand, as well as percentage of weeks with demand (non-zero values). Only weeks with demand (non-zero values) are used to calculate the mean, standard deviation, COV, and minimum demand to ensure the statistics were not affected by weeks without shipments. Next, a forecast check is performed (box 4) by analyzing the full length of available forecast data to determine the percentage of forecast weeks with a non-zero demand. This check is performed to filter out any SKUs that are being phased out of production.

These summary statistics are then used to determine whether the SKU is eligible for steady flow (box 5). If the SKU is found to be ineligible, it is marked as such and disregarded (box 6). If a SKU is found to be eligible, its optimal steady flow is then calculated (box 7). The optimal steady flow is chosen by maximizing total savings, which includes transportation savings, cross-dock savings, and cost of excess inventory. Figure 2 shows the calculations.
Definitions (units)

- \( n \) = # weeks in model horizon (weeks)
- \( s \) = number of pallets on steady flow (pallet)
- \( j \) = % of truck that a pallet represents – based on weight and volume (truck/pallet)
- \( p \) = transportation savings per truck ($/truck)
- \( d_i \) = demand for week \( i \) (pallet)
- \( c_s \) = cross-dock savings per pallet ($/pallet)
- \( c_e \) = cross-dock eligibility: \( 0 \leq c_e \leq 1 \) (dimensionless)
- \( e_{(i-1)} \) = excess inventory running total in week \( i-1 \); \( e_0 = 0 \) (pallet)
- \( h \) = inventory holding cost ($/$/weeks)
- \( v \) = inventory value ($/truck)
- \( r \) = end of period risk factor (%)

Optimal steady flow is calculated for every eligible SKU. An optimization is then performed to select the best mix of SKUs that maximizes total savings while conforming to a minimum vehicle capacity utilization constraint. This collection of SKUs and their corresponding quantities for steady flow is the model’s final output and recommendation (box 9).

The first six months of weekly steady flow is studied to calculate the average and minimum number of trucks/containers required for the steady flow of products. Once the steady flow of containers is determined, it is used as an additional constraint in the final SKU selection process (box 8).

Test Lane Results

The methodology developed was tested using data from the sponsor company’s North American operations. One high volume plant-to-warehouse lane with more than 1,000 SKU was chosen to calculate the steady flow using a set of input parameters, and the impact on the model’s performance when changing those parameters was studied. Figure 3 shows the optimization result for a sample SKU. As the steady flow increases to up to 9 pallets a week, the transportation and cross-dock savings continue to rise without incurring noticeable excess inventory costs. However, as the steady flow is increased beyond 9 pallets per week, the excess inventory costs rise rapidly. The total savings are maximized at 11 pallets per week. The optimal steady flow determined for this SKU was in between the minimum pallets shipped and the mean pallets shipped over the model horizon.

It was observed that as a SKU’s COV gets higher, the optimal steady flow moves closer to the minimum of the demand. As the variation in demand goes up, a higher steady flow increases the excess downstream inventory risk.

As the percentage of weeks with demand decreases in the model horizon, the steady flow also gets closer and closer to the minimum. In other words, the more weeks that have zero demand for any given SKU the closer the steady flow will be to the minimum amount of demand.
Conclusion
The goal of this thesis was to develop an analytical framework for determining the products that could flow on an intra-company lane regularly. This steady flow of products between supply chain nodes can lower transportation costs, increase cross-dock productivity, as well as dampen the bullwhip effect upstream in the supply chain. This research was done in the context of a plant-to-warehouse lane of a fast moving consumer goods company.

The methodology developed in this research utilizes historical and forecast data to characterize the demand. Descriptive statistics are used to determine whether a SKU is eligible for steady flow. Subsequently, transportation cost savings, cross-dock savings, and excess inventory considerations are used to optimize the quantity of each eligible SKU on steady flow. The model considers additional business constraints of vehicle capacity utilization and then recommends a final list of SKUs and quantities for the steady flow. This methodology was tested on a high volume plant-to-warehouse lane. Insights about the relationship between the variation in demand and steady flow were presented.

As the coefficient of variation decreases, the optimal steady flow moves closer to the mean of the non-zero historical demand and selected forecast over the model horizon.

Areas for future enhancements to this framework include optimal data aggregation, forecast accuracy implications, expansion of cost considerations, and implications on DRP. This research opens up the possibility of realizing cost savings by decreasing transportation costs and improving warehouse productivity, paving the way for innovative contract types with transportation providers. This framework allows shippers to bridge the gap between steady flow theory and implementation.

Figure 3 - Sample SKU Savings Optimization
Additional 2016 SCM Theses

Innovative Transportation Solutions: Uber for Freight
By: Leah Davis and Joseph Lucido
The transportation industry is constantly evolving, with new start-ups and technologies. One innovative transportation solution, Uber for Freight (UFF), seeks to more efficiently match shippers' loads with drivers and trucks through application-based algorithms. This research (1) defines the UFF model and its major players and processes, (2) distinguishes UFF from a traditional broker, and (3) analyzes the applicability of UFF to the sponsor company, a large multinational chemical seller.

Analysis of Inefficiencies in Shipment Data Handling
By: Rohini Prasad and Gerta Malaj
This thesis analyzes the errors that occur in shipment data for a freight forwarder. We used descriptive and predictive analytics to identify the relationships between shipment attributes and errors, and to predict the likelihood of errors. We used data visualization, K-means, Naïve-Bayes classifiers, and neural networks in our analysis. Results suggest that neural networks are the best predictive model for analyzing error in shipment data.

The Value of Monitoring in Supply Chains
By: Tarun Tiwari and Anthony Toteda
This thesis focuses on how logistics companies can use real-time sensors to generate business value. We found that customers are unwilling to analyze the data from these monitoring devices themselves. They want their logistics provider to interpret the data to provide value-added services. Therefore, logistics providers should leverage all the data they collect. To do so, we propose using smart contracts on a permissioned blockchain to automate business processes and reduce frictions between shipping parties.

Understanding Carrier Strategy and Performance
By: Caroline Bleggi & Qian Zhou
In this research, binary logistic regression and clustering analysis were used to identify individual and groupings of freight attributes that impact performance in terms of on-time delivery, on-time pick up, and first tender acceptance rate. Analysis of shippers' portfolios of carriers gave insights into the freight strategies employed and their subsequent service performance. These insights can inform future evaluation of the metrics used to understand the relative performance of carriers in different roles.

Capacity Planning for Biologics -- from Demand to Supply
By: Sifo Luo
This thesis provides a tool to capture both demand and supply uncertainty in pharmaceutical long-range planning. A stochastic optimization approach was used to minimize deviation from target capacity limit under different manufacturing and demand scenarios. The mixed integer linear optimization model incorporates the impact of demand and manufacturing variation on production allocation among manufacturing facilities through Monte Carlo generated scenarios. The model can be used as a tool to perform robust capacity planning.

Meeting Future Patient Demand for Drugs in Development Now
By: Emily Chen
The thesis sponsor, a large global pharmaceutical company, wanted to assess future manufacturing capacity risk for drugs in early stages of development. In this research, a discrete event simulation model was built to simulate active pharmaceutical ingredient production quantity outputs given varying levels of stochastic parameters. The results can be used to better inform capacity planning decisions.

SKU Stratification Methods in the Consumer Products Industry
By: Jiaxin Jiang and Andrew Steverson
This thesis explores SKU stratification methods that consider multiple SKU characteristics. We applied four methods (Single Factor, Dual-Matrix, Analytical Hierarchy Process, and Clustering) to the data from our sponsor, a Consumer Packaged Goods company. The Analytical Hierarchy Process is the most viable and comprehensive method for stratifying SKUs. It allows for a flexible number of stratification factors, different importance levels of the factors, and user control of the number of classes and class sizes.
A Generalized Framework for Optimization with Risk
By: Damaris Zipperer and Andrew Brown
In high-tech capital construction projects, the construction of facilities requires complex project schedules, forecast well in advance. These forecasts are used to hire contract workers. Traditional optimization solutions provide a starting point, but cost-efficient solutions require a more robust approach. This thesis proposes a risk integration methodology for contract workforce hiring optimization. The approach can be generalized to address other supply chain problems.

Drug Serialization Impacts Under Decentralized Data Management
By: Meng Ying Chang and Raghavendran Mohan
Our thesis evaluates the impact of the 2013 Drug Supply Chain Security Act on the pharmaceutical supply chain in terms of operational cost, IT infrastructure cost, and capital investment. We compared two information flows (centralized and decentralized) and two physical flows (unit level and Matryoshka). A unit level model under centralized flow bears the highest cost, as it requires highest IT investment. In contrast, a Matryoshka model under decentralized flow has the least supply chain impact.

Capacity Management and Make-vs.-Buy Decisions
By: Fady Riad and Akansha Nidhi
This thesis takes a fresh look at the make-vs.-buy decision-making process. We examined the assumptions underlying our sponsor company’s make-vs.-buy decisions and tested these hypotheses using product data. We identified assessment criteria that are both intrinsic and extrinsic to the decision-making process. Finally, we developed an analytical model to assist in evaluating make-vs.-buy decisions.

Simulating Inventory versus Service Risk in Medical Devices
By: Xiaofan Xu and Maria Rey
Medical device companies struggle to balance inventory and service performance, as the products are non-interchangeable and inventory investment is expensive. To find the right level of inventory, we first used an unsupervised clustering method to find demand pattern uncertainty for each product. Then we developed a simulation-based approach to determine required inventory to achieve a target service level guarantee. We produced a data-driven simulation model to help the sponsor company reduce inventory.

Designing a Multi-Echelon Inventory Distribution System
By Patrick Scott and Boxi Xu
This thesis examines the flow of raw materials and finished goods through the supply chain of a multi-national oilfield services company. We studied a centralized inventory approach, assessed through heuristics, against the company’s existing decentralized approach. We show that demand aggregation and lead time are important factors in determining the upper echelon for a company’s internal distribution model.

Forecasting International Movements of Returnable Transport Items
By: Patrick Jacobs and Rajdeep Walia
This research focuses on developing a one-month-ahead forecasting model to predict international movements of Returnable Transport Items (RTIs) between the US and Canada. Macro-economic variables, such as foreign exchange rate and GDP, were used to predict the number of international RTI movements. In addition, more traditional and validated forecasting methods were also utilized. Ultimately, 36 unique forecasting models were developed and compared using MAPE, MAD, and MASE metrics.

Unlocking Value in Healthcare Delivery Channels
By: Qi Zhang and Muching Zhang
Our thesis objective was to help our sponsor company, a “Big Pharma” company, understand the key cost drivers of their current distribution channel. We also explored the impact, from a financial and operational standpoint, of a shift to an alternative distribution channel. We show that a cost-to-serve model can be an effective tool if a pharmaceutical manufacturer is considering an omni-channel distribution strategy.

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