Separating Signal from Noise: Material Demand Forecasting and Network Simulation in a Multi-Echelon Supply Chain

by

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Abstract

Mismatches between forecasted and actual demand, for construction, repair and maintenance work in a regulated utility, is a growing risk for the performance of the supply chain. High target service levels and high levels of demand uncertainties necessitate Inventory Management to maintain a significant amount of safety stock to buffer against uncertainties. Furthermore, the increasing complex of supply chains make it difficult to anticipate possible effects changes, such as improved forecasting or policy changes.

In this thesis we propose an innovative approach for demand forecasting by creating a predictive model based on identifed patterns of repair and maintenance projects underlying the demand data. We further present a unique approach to simulate an overall supply chain, using locally available data, giving the supply chain the ability to evaluate the implications of improved forecasting on the overall network.

Through the improved methodology the supply chain can reduce the amount of noise in the data and create a forecast based on data that better represents the real demand. The proposed method improves on current forecasting methods by reducing forecasting noise, such as bullwhip and human error, by tying the forecast for material demand to the forecast of the source of the demand. To do so, we use unsupervised clustering K-means to identify similar consumption behaviors in the data. We further propose the use of a time-series analysis and hierarchical forecast aggregation for the creation of the final forecast, although this will not be the focus of this thesis. Although the results of the clustering process were inconclusive, we present data that supports the validity of out premise and propose alternative algorithms that could produce superior results.

In addition we propose a supply chain network simulation to validate the model and valuate its affects. We use the model to emulate the possible effects of forecast improvements on the overall supply chain

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Chapter 1. Introduction

This thesis is based on a six-month research project in a supply chain at a gas and electric utility company.

Supply chains in utilities provide ground crews with the needed equipment and material to perform regular and emergency repair jobs, to carry out scheduled maintenance, and to install additional infrastructure to support or increase network capacity. The magnitude of work associated with these jobs is expected to grow in an increasing rate due to natural growth in demand, aging infrastructure and an increased rate of extreme meteorological events. In order to support the crews, inventory management needs to maintain a inventory in the sufficient amount and diversity to fulfill demand in a short response time and with a high service level. However, with limited visibility into the demand generating processes and with increasingly an increasingly diversification of inventory, Inventory Management (IM) is facing significant misalignments between forecasted demand and actual demand, which can potentially compromising their service level. Furthermore, previous research has shown that data distortion is proportional to the number of steps it is observed from the source, further adding to the problem.

We propose that we can alleviate this issue using machine learning by identifying underlying patterns in the data, associating them with consumption behavior, and creating a forecast using these new insights. In this thesis, we present an innovative methodology to forecast actual demand, reducing the risks and challenges of the bullwhip effect in multi-echelon supply chain in a regulated utility. In addition, offer an approach to evaluate the implications of such an improvement on the overall supply chain, using a discrete event simulation to model the behavior of, and implications on, the rest of the supply chain network.

The optimal solution, however, is not to create this insight from obscured patterns in data but to gain actual visibility to the demand. In order to demonstrate that gaining actual visibility into demand is improbable in the coming future, in this thesis, we first give context to the problem. In Chapter 1, we discuss the challenges facing the utility industry and its implications on the performance of internal supply chains. An account of the current state, characteristics, and scale of the infrastructure is given along with how it facilitates growth in the magnitude and variation of material demand. We further detail the current and expected changes in the industry that could increase the uncertainty in the demand. Finally, we present the problem statement, approach, and contributions of this thesis. In addition, in Chapter 2 we give an account of the organization, setting the environmental context, challenges and constraints of the problem. Doing so we present an organizational analysis of organization as a whole, in addition to the supply chain group. We further describe the internal processes, flow of information and material, and priorities. In this chapter, we briefly discuss how these aspects of the contribute to the generation and amplification of the problems faced by the supply chain team.

After a discussion on the relevant literature in the fields on the subjects of supply chain, forecasting and discrete event simulations, we present our methodology along with significant insights on the data available. In this section we give a detailed account of the steps in the methodology along with the justification. We conclude the chapter by detailing the challenges with the data and outline several possible solutions for future studies.

In addition we present an approach for validating the previous methodology and valuating its effects on the complete supply chain through network simulation.

1.1. Background

In the following chapter, we begin by laying out the background to the work, we provide a brief overview of the Electric Utility Industry in the United States, the company, and it is Supply Chain. Following, we discuss the problem addressed, propose an approach and discuss the contribution of the work. Concluding this chapter is an outline of the work.

This following section includes a description of the electric utility industry. We describe the sheer magnitude of the electric grid in the United States alone, we present the primary functions within the sector, as well as discuss the business model. The following section we discuss the primary drivers, the compensations, and the incentives for utilities. The understanding of these structures is fundamental to the understanding of the priorities within a utility.

We continue to in describing the drastic change between the dormant state the industry has been in over the past 100 years and what are the changes that have occurred in the past ten years. We further discuss the implications of some of the changes that have occurred in the past several years and discuss an outlook for the near future and discuss the challenges that this sector, and the companies within it, will be facing in the coming years.

Lastly, we provide an overview of the function and responsibilities of supply chain and inventory management (IM) within a utility. Doing so, we define the scope of the supply chain, for the purpose of this thesis, and conclude this section by touching on some of the key challenges that this group is currently experiencing and some that the group is expected to experience in the future.

In Section 1.2, we discuss the problems addressed in this thesis. We describe the misalignment between demand from planned projects, forecast, and actual consumption; we discuss the causes of this misalignment as well as describe some of its effects on the supply chain and the rest of the organization. We further provide an assessment of external and internal forces that can aggregate and cause these misalignments and discuss possible outcomes.

In Section 1.3, we present our approach for solving the problem. We describe a novel approach that uses machine learning, and data mining, techniques to create an aggregated demand forecast by forecasting the elements that generate the demand as well as detail the steps and stages to implement the methodology. We further describe the steps to create a simulation model for the supply chain to evaluate the effects of changes to the supply chain, such as the proposed forecasting method.

In sections 1.4 we present the contributions of this thesis to the field as well as to the company, followed an outline of this thesis In Section 1.5.

1.1.1. The Utility Industry in the US

It has been said, not without cause, that if Thomas Edison had risen from his grave, he would not have noticed a difference in the electric grid.

The US electric grid described as the Greatest Engineering Achievements of the 20th Century by the National Academy of Engineering. With over 500 electric transmission companies and 1,100 and distribution companies, it entails over 120,000 miles of continuous electric power transmission. Consisting of three primary parts – generation, transmission, and distribution.

In the following section we present a brief overview of the Electric Utility Industry in the united states, we show a brief description of the company, and we give an outline of the Supply Chain function within the industry.

1.1.2. Electric Generation

In the traditional model, the generation of electricity is produced primarily in thermal powered power plants through the incineration of fuels, such as coal or gas, to convert water into steam that drives an electric generator. Since the introduction of AC long-distance transmission at the end of the 19th century, these power stations were frequently positioned far from the primary consumption source, such as a city center, in order to avoid high real-estate costs and to take advantage of economies of scale. Today, with the continuing advancements of generation technologies, such as renewable, gas and bi omass-based generation, the production of energy is transitioning closer to the point of consumption. Since the 1990s, when utilities were mandated to allow all generators access to the grid, the generation is considered a competitive market.

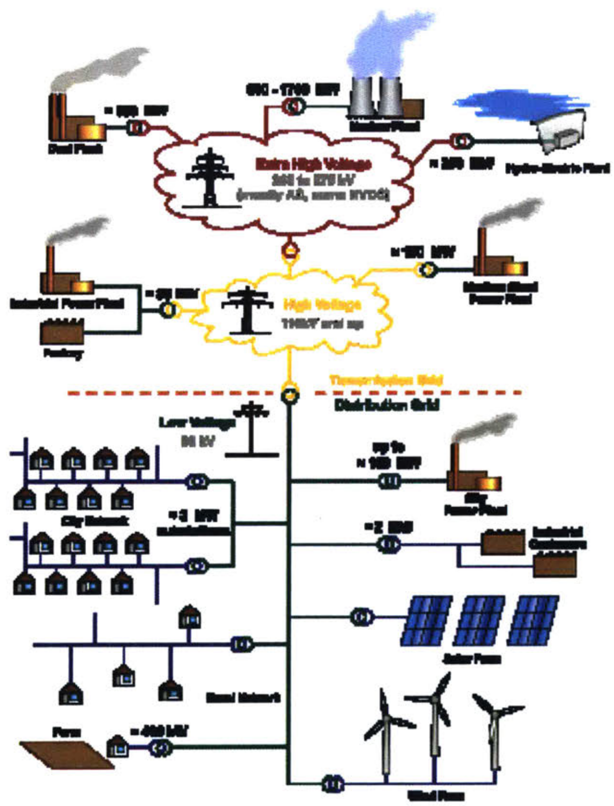


Figure 1-1: Electic grid from generation to consumption

1.1.3. Electric Transmission

Introduced first in 1890, AC transmission provided a way of transmitting high voltage, typically above 115kV, over a large distance with very little power loss. The electric transmission grid connects between the large, usually distant, power generators through substations, which convert the electricity from passing to local distribution networks.

1.1.4. Electric Distribution

Electric distribution networks are the low voltage, typically under 50 kV, grids that connect residential and commercial customers to power sources. In order to maintain a limited amount of power lines, poles, and transformers, on public streets, the distribution network for a region is managed by a single regulated company.

1.1.5. The Business Model

Electric Utilities, which may include investor-owned, publicly owned, government-owned companies or cooperatives maintain and operate the infrastructure that provides the delivery of electricity from power sources. The utilities are responsible for maintaining the infrastructure, handle breakdowns, and assure that the grid is capable of transferring the needed electricity from the point of generation to the consumers. In most cases, however, although the utility solely owns the infrastructure capable of transferring the electricity, they cannot charge monopoly prices for this service. Instead, regulatory entities, such as the state regulatory commission and the Federal Energy Regulatory Commission, decide on the rate that consumers are charged in a process called rate-making.

The regulatory entities represent the public interest, governing the utilities. Deciding on subjects such as the infrastructure program plans, for the utility to implement, performance measurements and an acceptable Return on Equity, which is the maximum compensation the utility can achieve. In addition to allowing a viable business model for the utility, the objectives of the rate-making are to attract investor capital, assure reasonable pricing, controlling level of demand and often to incentivize performance.

The compensation model for each utility can vary according to differences in the social, political and environmental factors in which they operate. In general, the compensation models usually entail at least the following two aspects:

1. Compensation on installed capital
2. Compensation on operational expenses

The compensation on installed capital usually comes in the form of an agreed-upon rate interest on capital installed in the utility network and is usually referred to as the utility's allowed ROE. This ROE compensates the utility for approved investments they make to upgrade existing infrastructure or to install new infrastructure to support demand growth. Consequently, it is in the utility's interest to install as much capital, in infrastructure, as is approved in the rate-making process.

The compensation on operational expenses usually covers a significant portion of the utility's operational expenses and is often linked to a benchmark on comparable expenses. The objective of this compensation is to assure that the utility does everything it needs to keep the grid operational. Because in the pure form of this clause, it incentivizes inefficiencies, additional clauses are usually in place to promote operational effectiveness, such as a performance and customer satisfaction metrics. However, these factors do not always do not always induce the intended outcome.

1.1.6. Winds of Change

Regulators and utilities alike, are driving reform and innovation onto a once dormant industry. Growing awareness to climate change, improvements in technological, customer expectations, have pushed the industry from one of the most conservative industries to one that is constantly looking for a change. Regulators across the country are setting ambitious commitments to significantly reduce greenhouse gas emissions, inviting experimentation with new models and technology, and emplacing Energy efficiency programs. The utility, as the point of contact between the customer and the market, has been charged with increased responsibilities in accommodating and even driving these changes.

Similarly, many utilities have identified this coming change and have embraced the challenge with both arms. Utilities are investing time, effort, and capital, into projects such as

Neighborhood solar, Micro-grids, and Smart grids, models that were once considered a threat to the industry.

1.1.7. Supply Chain at a Utility

In the following paragraphs, we describe the function of a Supply Chain at a Utility, Inventory Management, and the challenges they face.

1.1.8. Supply Chain

In order to ensure the continuous delivery of energy supply to the customers, utilities continually engage in maintenance, repair, and upgrade of the existing network, as well as in the installation of additional capacity (i.e., new lines, substations, and so forth) in order to meet growing demand.

The Supply Chain organization is responsible for supplying the crews in the field with the bolts, safety vests, pipes, transformers, or any other material; they need to complete their work. The cost of not meeting this responsibility is high and may include losses due to idle crews, regulatory fines, and liability due to prolonged outages for electricity and gas customers.

Supply Chain Network

The below diagram (Figure 1-2) is a simplistic representation of the supply chain network extending from the supplier to the crew trucks and projects. For the purpose of this thesis, we divide the supply chain to three parts: Supplier side, which includes all external supply chain up until the arrival of the material on the incoming dock of the CDCs (CDCs); the internal supply chain, which spans from the CDCs to the first tier of storage that serves the field crews dubbed crew barns or Independent Business Units (IBUs); and third the side of the supply chain is at the regional company level, which includes everything between the IBUs and the installation of the items at their final destination.

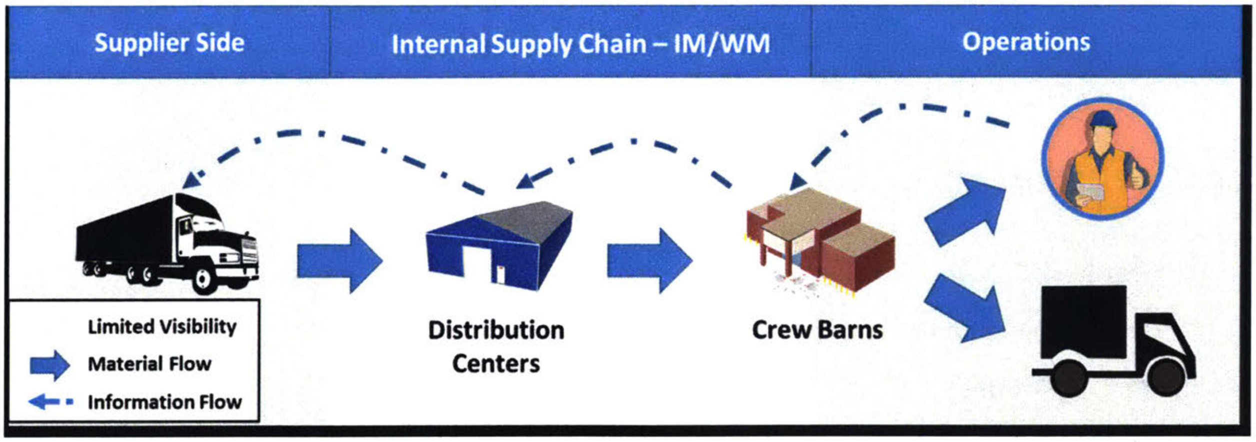


Figure 1-2: Scope of the Internal Supply Chain

Inventory Management

The IM Group is responsible for stocking the CDCs with the right material at the right quantity at the right time. Key metrics include Inventory Turns, Material Availability (or service level), Stranded Inventory, and Supplier on Time Delivery.

Supply Chain Challenges

The challenges I the supply chain could be bucketed into three categories: uncertainties in demand and supply; capacity and flexibility; and change management. In this thesis, we address the subjects of uncertainties in demand as well as the subject of Capacity.

Key Challenges in the Supply Chain

In a supply chain, variance, caused by uncertainties in the system, is one of the primary levers affecting network performance. Additional levers for network performance are target service levels, assets, and processes. In the supply chain evaluated several sources for uncertainties were identified. Here below is a list of sources we identified:

Supply Uncertainties

I) A limited number of authorized suppliers
II) Difference between contractual and actual lead times

III) High variability in actual lead times

IV) Increasing offshore material sourcing

Demand Uncertainties

I) **Network Design**

Highly diversified between regions, counties, and towns.

II) **Forrester Effect**

Additional layers of storage between the CDCs and the end use causing a bullwhip effect, increasing variance in the observed demand signal.

III) **Crew Work Plan**

Work schedule created by a resource planner is updated on a day-by-day, and sometimes hour by hour, basis at each crew site. Short term planning reduces the time horizon available to obtain material supply.

IV) **Weather Conditions**

Increased risk of extreme events, which highly influence demand.

V) **Grid Innovation**

Growing diversification of network designs due to experimentation with new grid technologies and models.

Additional Challenges in the Supply Chain

Upholding a specified service level necessitates the supply chain to maintain an appropriate level of reserve storage capacity in the warehouses, in proportion to that of the service level. The unutilized capacity can then be used to buffer for internal and external variability in a supply chain, such as, storing material for a project that has been postponed for three months, or have the capacity to stock up for winter. For example, This reserve capacity is expected to become increasingly limited with time due to the aging of the network, the growing electricity demand, and the growing material demand.

A significant proportion of the infrastructure installed in the US has been installed between the 1940's to the 1960's. Although the expected lifespan of this equipment should be ~40 years, it is costly to replace all of it [1]. Although efforts on company, state, and federal levels, are underway to progressively replace the equipment, the rate at which it is undertaken is intentionally slow so not to overburden taxpayers. As a result, the average age of infrastructure is and will remain high driving an increasing rate equipment failure, increasing number if repair-work carried out by ground crews, and an increasing amount of material needed for this work.

In addition, there is a constant growth in electricity needs driven by the growth in population, industry and commerce. Although this growth by itself is not substantial, averaging at an annual rate of 0.4% across the US, its effects of on the inventory requirements is compounded by the increasing versification in inventory.

Lastly, from the perspective of system dynamics, the demand for material continually grow irrespectively to the actual need. From a behavioral point of view, every time the supply chain is not able to deliver the right material at the right time to the right place, ground crews will be pressured to increase the levels of internal inventory, in order to avoid the possibility of delays of future projects. These internal inventory locations are often informal and unseen by the supply chain controllers. To stock up on internal inventory levels the personnel will inflate orders that will increase the forecasted demand baseline causing the supply chain to increase inventory of items that will not necessarily be ordered. Subsequently the limited warehouse capacity is taken up by items not in demand substituting high varaiaty small, but adequate, quantity to limited variety and high quantity. The reduced flexibility increases supply chain difficulty to provide the right items at the right place at the right time in the right quantity.

1.2. Discussion of the Problem

The company's supply chain is facing frequent misalignments between planned, forecasted and actual demand in terms of both material types and quantities. The multi-echelon structure and decentralized control of the supply chain obscures both the actual demand and the inventory levels throughout the supply chain, from the IM team. Unable to observe the actual demand, the IM is forced to create a demand forecast based on high level asset management plans as well as material demand data from the CDCs.

However, the confidence in both sources is low. The projects planned by asset management are frequently postpone or replace, limiting the confidence in its projections, and inventory holding locations on lower echelons of the supply chain magnify the already high levels of demand uncertainties from external factors resulting generating a significant bullwhip effect. Consiquntly, the internal supply chain team need to maintain an increasing level of inventory, and rely on material expedition and redistribution, to maintain their required service level.

In addition, limited visibility into the lower layers of the supply chain hinders the ability to assess the conduct and evaluate the performance of the supply chain as a whole, creating a gap in information impairing the organization's decision making abilities. Furthermore, the information gap harms the ability to quantify the actual effects of changes and other decisions having a partial pucture of the implications. In the best case, the information gap takes shape as lack of information, which increases the uncertainties of the decision un question. In the worst case, however, the gap takes form as partial information seen as complete picture, which causes the uncertainty in the decision to be replaced with increased levels of error.

The problem that we address, therefore, is two folds:

I) Challenge in forecasting demand from noisy data causing frequent misalignments between predicted and actual demand; and
II) Difficulty to evaluate the effects of changes to the supply chain

1.2.1. Forecasting Demand from Noisy Data

In order to support the ground crews at the required service level, the company's IM team is required to maintain an appropriate amount of safety stocks to buffer for uncertainties.

These uncertainties include high variance in order frequency and quantity, which present themselves as unanticipated large and urgent orders, driving safety stock up.

In the industry, demand forecasting is showing increasing predictive capabilities in anticipating demand. However, the current processes necessarily includes forecast biases and miscalculations of tiers that precede the scope of the internal supply chain. The implications are that the team is:

I) Using a forecast that is based on a misrepresentation of the demand, rather than the true demand, resulting in reduced ability to predict unplanned work.
II) Planning inventory levels based on an amplification of the uncertainties in demand, which drives up the required level of safety stock.
III) Magnifying the bullwhip effect to their suppliers, increasing long term prices and rates

Furthermore, increasing growth in annual demand quantity and in variance of both demand and supply, is expected to increase the amount of cycle and safety stock needed, thus reducing the flexibility and resilience of the supply chain. These increases, in quantity and variance, are a result of several sources. First, on the demand side, increased in order quantity is caused by a progressively aging network, increased weather related deterioration, and natural growth in population; while increase in uncertainties is produced by an increase in the frequency of severe storms and an increase in grid complexity. Increased uncertainties in supply include longer lead times and potentially reduced punctuality in order fulfillment, due to an increasing number of SKUs sourced offshore.

Long-term initiatives to align processes, systems, and technologies across the company may realize fruitful in aligning supply and demand. However, the extent of the effects and certainty of the success of these initiatives are not certain.

1.2.2. Evaluating the effects of changes to the supply chain

Lack of transparency between echelons hinder the ability to evaluate or quantify the performance of the supply chain as a whole. In attempt to maintain a high service level for the final customer and perhaps because of the fragmentation of the systems and procedures in the company, numerus formal and informal inventory storage locations have propagated throughout the system. In addition to the magnification of the bullwhip effect, these additional inventory locations entail hidden costs in material handling, holding, wear, transit and more.

One concern with the inability to evaluate the performance of the supply chain as a whole is in making decisions based on incomplete or no data, or evaluating the effects of these decisions. In the past, for instance, previous improvements that reduced material prices have had limited effect on the bottom line costs associated with material usage. It is suspected that the source of these hidden costs in this unobserved part of the supply chain.

1.3. Approach

To solve the problem, we propose a two stage solution, where the first we create a demand forecast for material using data mining methods to isolate consumption patterns from the enveloping noises in past order requests; and the second stage uses network simulation to validate the results of the first stage and its effects on inventory.

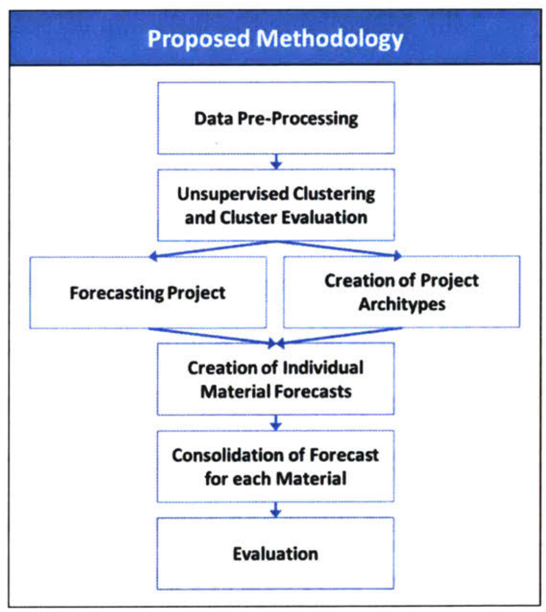


Figure 1-3: Proposed Forecasting Methodology

1.3.1. Demand Forecasting based on noisy data

In order to create a demand forecast for material, we propose a three-part methodology:

I) Identifying and categorizing similar material consumption profiles, i.e. similar types and proportions of material, from historic demand logs and differentiating them from environmental noise;

II) Analyzing the behavior of the individual categories over time and creating a forecast for each category;

III) Combining the forecasted consumption into an aggregated material forecast

As described in the discussion of the problem, the demand signal, observed by the unit as order requests received from the preceding tier, is noisy and bulky entailing layers of noise and distortion resulting from the distance from the point of generation. We decompose the method into five steps.

The first two steps, which will be further described in Sections 4.2.1 and 4.2.2, are intended to uncover the underlying patterns in the historic data. The latter three steps translate the uncovered patterns into a forecast for material demand. These last three steps will not be the focus of this thesis but will be discussed and outlined in Section 4.2.3.

Data Preprocessing

The first step entails the processing of the raw data to data suitable for analysis through machine learning algorithms. In this step, we clean the data, in order to assure that the learning algorithm is not biased by data that is not representative of reality, such as outliers, false positives or negatives, and so on. We restructure the data to fit the method of the intended algorithm, and we impose linear transformations to reduce complexity and improve resource usage. We will go in to further detail in Section 4.2.1.

Demand Signal Segmentation

The objective of the second step is to identify and categorize similar material consumption profiles in the data. For this purpose, we implement an unsupervised K-means clustering algorithm for the identification of similar consumption profiles and validate them with subject matter experts. Once validated, we create appropriate project archetypes, which include material consumption profiles; variances; and confidence intervals, and label the data for future analysis purpose. This will be discussed in Section 4.2.2.

Segment Analysis and Forecasting

In the third stage, we analyze each project group, using a time-series analysis, and create a forecasting model to predict the occurrence of these each project architype over time.

Material usage forecast aggregation

The last stage of the methodology is to aggregate the expected material usage of each project architypes into a comprehensive material demand forecast.

We present an outline and discussion of these last two steps in Section 4.2.3.

1.3.2. Evaluation through Network Simulation

The approach chosen to evaluate the effects of the proposed forecasting methodology is to model the current supply chain network and simulate alterations with stochastic processes. Network simulation has long been recognized as a method to test "use-cases" [2], [3] and will not only provide us with the bottom line valuation of the benefits of the proposed forecasting methodology, but also it will also provide some insight into the behavior of the different layers of this supply chain and how they interact.

The method adopted for this stage is as follows:

I) Identify Supply Chain Parameters, Variables, and Objective Function
II) Map Supply Chain Network
III) Build Model
IV) Model validation using a deterministic process
V) Evaluation of forecasting methodology using a stochastic process

The model, which will be described in detail in Chapter 5, will receive as inputs cost data, financial information, issuance and receipt logs, inventory levels, as well as information on SKUs and storage facilities. Its outputs are comprised of supply chain costs, including holding costs; trucking costs; expedition costs; and penalty costs for unavailable stock, KPIs, including Inventory Turns, as well as Fill and Obsolete rates.

1.4. Contribution of the thesis

The contributions of this thesis span through the fields of demand forecasting, network simulation and industry.

In this thesis, we propose a novel approach to demand forecasting for a supply chain with an underlying demand generating process. The proposed approach can to the field of material planning is especially warranted in cases where the underlying demand is generated by events with recurring consumption profiles, e.g. projects.

We further propose a method to scale localized data to a overall supply chain. In this we present an algorithm to account for, and optimize, supply chain fulfillment procedures. In addition the subsequent tool will allow the company to simulate the supply chain subject to different changes, such as increased demand or extended lead times. This will allow the users to evaluate the effects of these changes, as well as possible mitigation techniques, to the supply chain.

1.5. Key Insights and Outline of the Work

The performance and service levels of the supply chain group are at risk of deteriorating due to growing pressures on capacity. The growing electricity demand, aging infrastructure, and increasing uncertainties in supply and demand increase the number of executed projects, increase the versification of SKUs and, in general, increase the need for cycle and safety stock. Insufficient spare storage capacity can hinder the supply chain's ability to absorb degree of variability in demand.

The thesis is organized as follows: In Chapter 2 an analysis of the organization is presented, in addition to additional descriptions of processes in the supply chain organization of the company. In Chapter 3, we give an overview of current literature on supply chain performance, statistic-driven simulations, and tools and techniques used for simulation. In Chapter 4 we present a detailed description of the model simulated, it's build, and results. And in Chapter 5 we present the conclusions from the findings, their implications, and offer recommendations.

Chapter 2. Organizational Analysis

In this chapter, we present additional context for this thesis. We provide a description of organization dynamics that lye in the root of the some of the issues that are underlying the company.

We start with a brief overview of the utility at which the project was conducted, how it was established. In this section we provide some context to the initial causes that drives many of the challenges that the organization is facing today. We continue by placing he supply chain into the organizational context, providing a short account of the it's structure, in addition to the different positions that comprise it.

We continue with organizational analysis, using the three lenses model developed at the MIT Sloan School of Management. We start with a brief description of the model and the different perspectives taken to account when making this analysis. We continue in analyzing the company with a strategic perspective, a politivcal perspective and finally a cultural perspective.

In Section 2.3 we provide a detailed account of the internal processes of the supply chain, the flow of information and materials. In adition we describe the different actors that take part in the movement of material from the CDCs to where it is finally installed. We continue in describing how the supply chain sees and measures itt's performance and finish by proding a sythtasys of the causes and effects that create the callenges the team are faced with.

2.1. Company Overview

Establishing its presence in the US market late in the 20th century through the acquisition of local utilities and service companies, the company is one of the most predominant investor-owned utilities in the world. With a global footprint, the company maintains a network that spans across 200 thousand miles worldwide, connecting more than 20 million people to energy sources. In the US the company maintains a service area that spans across several states, with transmission and distribution networks that span over 130 thousand miles.

The company is tiered into several strata. The US wide company, which is owned by a global holding company, do not undertake any of the field work, but rather serves as a holding company for regional subsidiaries. In addition, the company provides the regional companies with services, such as supply chain, legal, design and planning. There are over 15 subsidiary regional companies and service companies that are held under the US parent. The challenge of consolidating the legacy companies, in terms of policies, processes, and procedures has proven difficult. Although the different companies have been working under the same name for over a decade, they still act, in most part, as different companies and maintain many of their legacy "habits". Another challenge is the separation between the different Lines of Business (LoB), as in between Gas, Electric and Generation.

2.1.1. Supply Chain

Until recently the US procurement organization nested within it two groups: Inventory Management (IM) and Warehouse Management (WM). Currently, a VP of Supply Chain is in place with the two groups reporting to him Figure 2-1: Procurement Organizational Chart - Supply Chain.

The WM group entails the five CDCs that supply the different service areas of the company, as well as an Investment Recovery facility. From the five CDCs, one supplies exclusively gas material to its region and one supplies exclusively electric material to its region. The remaining three CDCs supply their service area with both electric and gas material.

IM, includes a planning group as well as several analysts and project managers, responsible for efficiency projects for the group. The planning group entail material planners, who are responsible for maintaining the right levels of the inventory that is needed in the warehouses. The planners are divided both by region and by Line of Business, i.e. gas/electric, distribution/transmission. In addition, there are several expeditors, who are responsible for attaining ordered material that would not be available in time.

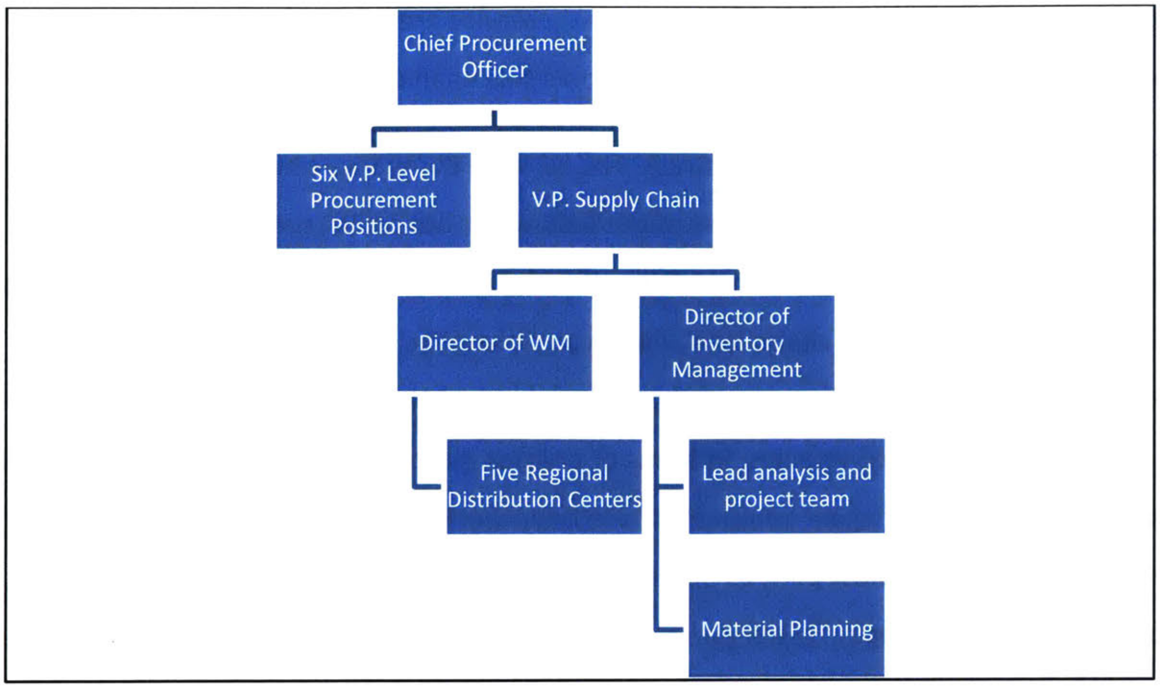


Figure 2-1: Procurement Organizational Chart - Supply Chain

In addition to the primary groups, the supply chain makes use of additional company entities for its day-to-day work. These groups are, fleet, master data, accounting and finance.

2.2. Organization, A Three lens analysis

Organizations are complex organisms made of people, goals, and more. Ecosystems that encompass the intricacies of human interaction, meaning, function, structure and conflict that are not easily defined or modeled. In this section, we will analyze the organization with the use of the three lenses model [4]. In this analysis, we will observe the organization with different perspectives in an attempt to understand the organization in the eyes of the people within it and outside of it. These perspectives include the strategic design lens, the political lens, and the cultural lens.

I) The Strategic Design Lens

Through the strategic design lens, we assume that the organization is a machine. A mechanical system, which its parts fit well together to match environmental demands, designed to achieve defined goals. It is the rational division of people, money and equipment to efficiently, and effectively, achieve a planned objective. In this lens, we examine the structure of the organization, how the people, assets, and capabilities are grouped in order to achieve a defined goal; we examine the formal and informal mechanisms that link between different groups; and lastly we examine what mechanisms were put in place to align the efforts of individuals to the overall strategy of the organization.

II) The Political Lens

Through the political lens, we see the organization as a collection of diverse stakeholders with different and occasionally negating goals and underlying interests. Between these stakeholders, there is a constant competition for finite resources and a need to build power through coalitions between units, groups, and individuals with similar interests. Goals and strategies are negotiated. In this lens, power is the ability to get things done, either as a group or as an individual. In this lens, we examine internal and external stakeholders and their interests; identify existing and potential coalitions; and we assess the mechanisms and methods that are used to handle negotiations and conflicts.

III) The Cultural Lens

Through the cultural lens, we see organization as a social system that gains stature through the time and effort that the employees spend in it. A system that entails symbols, artifacts, rituals, values and routines, and, in light of these, gives meaning to our actions. The cultural lens describes the shared experience in the organization. Furthermore, it describes in what light are things perceived by the individual, the group, and the organization. In this lens, we examine what do people, and groups, hold as important.

2.2.1. The Strategic Design Lens

Bringing Energy to Life

The organizational structure of the company is a hybrid between hierarchical structure, used by the regional businesses, and a matrix structure, used for LoB. The structure is designed, on one hand, to create barriers between the different regulatory regions, and on the other hand, to retain engineering and technical expertise for the various lines of business, i.e. gas, electric, transmission, etc. This structure is, in part, designed to deal with the regulatory complexity of working across several regulatory regions, and in part, is a product of the acquisition of over 15 operating and service companies, which make up the company.

This organizational fragmentation also fosters a silo'ed mindset between the different units of the organization. The implications of this mindset is that units attempting to improve attain local optimization at the expense of the global good. An additional challenge is the barriers to transfer useful knowledge and data between silos making global improvements and organizational projects difficult to implement. The information technology and systems, for instance, that are used by the legacy operating companies differ from the one used by the service company. Although data connections are in place to bridge between the systems, the post transfer data is often filled with noise, including false duplication of orders, missing orders, SKU perliferation and more.

Furthermore, the silo mentality trickles down to the rest of the organization, creating misaligned incentive structures within the same unit. For instance, the Supply Chain organization is nested in the Procurement organization, where the former is incentivized to lower the Total-Cost-of-Ownership and the latter is to create least cost contracts. These two objectives, more often than not, do not meet.

There are however extensive initiatives to turn the company into a process-oriented organization. The goals of this transformation is to realign incentive structures and process management so they support processes from a system-wide perspective.

2.2.2. The Political Lens

A Changing Landscape

Almost a decade after the last acquisition there remains an enduring reminisce of the legacy companies. Of the senior leadership, a large majority have boarded the organization in the series of mergers that brought the company together and it is evident that there still is a group comradery. However subtle and thinned it has become, there is a shared history. These informal interpersonal connections between the leaders entail significant political power making these groups dominant in the organization. However, the fact that the people in these groups primarily originate from managerial and engineering positions at the operating companies, and therefore hold some preference to their old groups, presents a challenge for groups that have not traditionally fed this chain of command.

The supply chain team, which has not been central in the history of the company in its current or previous form, is one of these groups. As a result, the implementation of supply chain initiatives is reliant on the personal abilities of their leaders to successfully navigate the requirement labyrinth of the stakeholders, all from a point of disadvantage. Furthermore, any resistance from a person within the power group can quickly tip the scales and halt any process.

One example that will help depict a common situation for the supply chain. In an attempt to improve material ordering procedures, the supply chain initiated an effort to educate the field personnel and impose constraints on maverick ordering with the goal of instilling behaviors of advance material ordering. However, when an order came in for a long lead-time material, which the only available material had been ordered by another project, instead of postponing the project or rescheduling the use of the material to a later on in the project, orders from senior LoB management came in to reallocate the material from the original project.

Of course, many of these decisions are merit and priority based, but for two equivalent projects, where the price of not meeting schedule is high, such advantage can tip the scale. The implications are that not only do these imposed changes increase the uncertainties in demand but also the supply chain organization has little power to change such behaviors.

2.2.3. The Cultural Lens

A Service Company, Through and Through

For the past decade, the company has been trying to create a cultural identity that will meld together the legacy companies with the umbrella organization. Today, the atmosphere within the supply chain team as well as the rest of the parent organization, is that of service. *"Always keeping our customer in mind"*; *"helping our customer do their job better and safer"*; personal storm restoration stories; pictures and stories of employees with visiting ground crews or helping customers. Whether it is the end customer, or the direct customer – the Line of Business, service is celebrated and honored.

The integration, however, between the companies is far from complete. A change-averse culture, which has assimilated itself from the typical utility risk-averseness, facilitates a divided that has yet to be bridged. One symbolic example is that employees of the parent company still call the regional operating companies by their legacy name.

Furthermore, the Line of Business have yet to fully trust the "corporation" to take care of their interest. Inventory wise, for instance, the ground crews still accumulate material in their trucks and yards just in case the corporate supply chain would not live up to their commitments. Two events that have occurred over half a decade ago, a severe storm and an attempt to implement a company-wide information system in the past, are still referred to when field personnel are asked about self-stocking behaviors.

Building the identity aspects of organizational structure, such as routine coordination meetings within each team; "start with safety" procedure in each meeting; monthly departmental conference to communicate achievements, goals, leadership messages, as well as celebrate occasions, including number of years in the company. All of which help build the identity of the organization and the people within it.

2.2.4. Bringing the three lenses together

Although there are extensive initiatives to make the company more process oriented, implementing end-to-end processes; introducing new perspectives and skills by onboarding outside talent, at both the entry and management levels; and unite the company, there is still a long way before significant changes would be seen. The challenges that the company needs to overcome include an information system that is fragmented between regions and domains; organizational barriers that promotes local optimal solutions; a misalignment of incentive structures; and a cultural divide between the different groups.

In addition to the above-mentioned challenges, differences in regions, subdivides between the groups and regions of the company, as well as past issues bring about a certain amount of distrust from the field crews.

This distrust has several effects. First, any event in which the supply chain is not able to meet demand is amplified in the minds of the crews. Second, the reduced confidence proliferates the amount of hoarding and intermediate inventory in the system. And third, increases the risk of ineffective collaboration, where there is a collaborative coordination of the work, needs and resources but since the parties involved do not know how the other party will actually behave, the effects of the collaboration become limited, further sawing distrust between the groups.

2.3. Supply Chain

2.3.1. Information Flow

The information flow of material demand and need is characterized by a multiplicity of layers, systems, and human controllers. This complexity entails not only risks of misscomunication and translation issues between the different layers, but also buffers information transfers causing a delay between consumption and request. In the following section we describe the process material orders go through between the origin and the supplier.

The flow of information detailing the material needed, as depicted in Figure 2-2, may originate from one of the following sources:

I) Ground crews
II) Crew yards, if the local crews hold inventory on location

III) Projects

IV) Independent Business Units (IBUs)

V) Engineering

VI) Contractor supervision

The requests for material that are not sourced at the IBUs are either passed through an information system or verbally to the IBUs. There are three types of IBU inventory policies that all may apply to an IBU or none of them.

IBUs pace orders as needed through either through their legacy system or through the company ERP, by filling a "shopping cart". If the request was placed through a legacy system, it is passed to the ERP. The request is then passed both to WM, who fill the order, and to IM planners. Planners monitor the inventory levels continuasly and issue/approve order requests to suppliers when needed. If the inventory levels are expected to pass the reorder point for a certain material, the system notifies the planner if another CDC holds that item in surplus.

Material orders may also be received from different engineering and asset management groups that create project plans and designs. The orders may be automatically triggered by the system they work on, or may place manually place orders in case of material with long lead times.

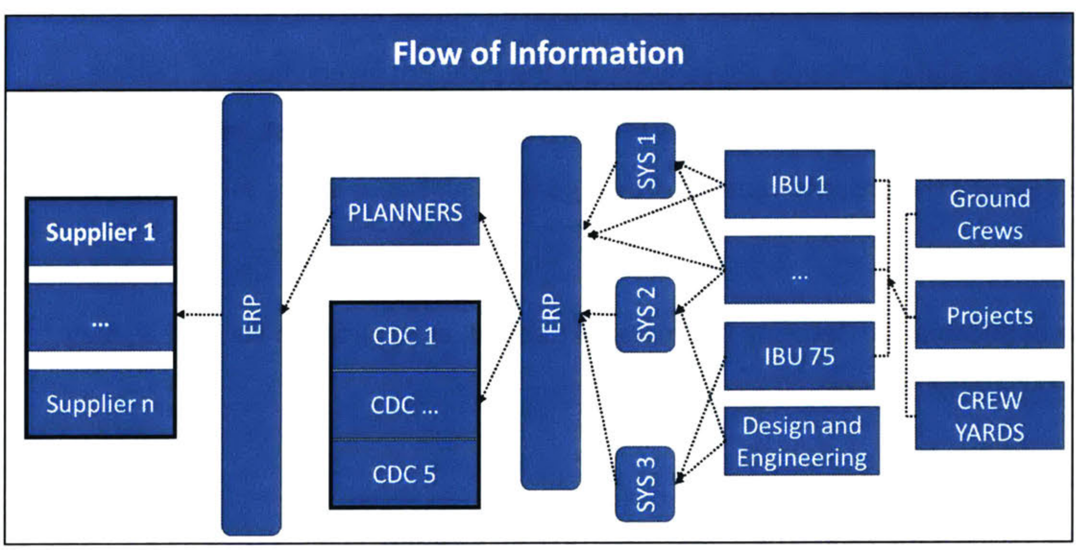


Figure 2-2 Supply Chain - Information Flow

2.3.2. Material Flow

Material that arrives at a CDC is accepted and registered in the system. The CDC runs trucking routes and supplies IBUs on a regular schedule. The frequency of delivery to IBUs run between one and several times a week. According to material request, the items are either stocked in the IBU inventory, or set aside for a specific project , or added to the "open bin" storage, which is inventory that is intended for crew members to access freely and collect items they may need.

The material is collected by the ground crews and contractors from the IBUs or the open-bins and brought to project sites, stored on the utility truck, or at other locations. If a storekeeper exists at the crew barn, she orders material from the regional CDC to maintain inventory levels otherwise the ground crews can order material as needed. Material planners, at the CDCs, maintain inventory stock; review orders for the coming week and tune reorder points in accordance to material forecasts and past experience.

Beyond the the CDCs only a handful of IBUs operate an inventory management system that allows visibility into their invenroy levels. Otherwise the supply chain has no visibility to what happens to the material beyond the CDCs. Furthermore, it is known that there is a phenomena of stockpiling at crew trucks and crew locations downstream.

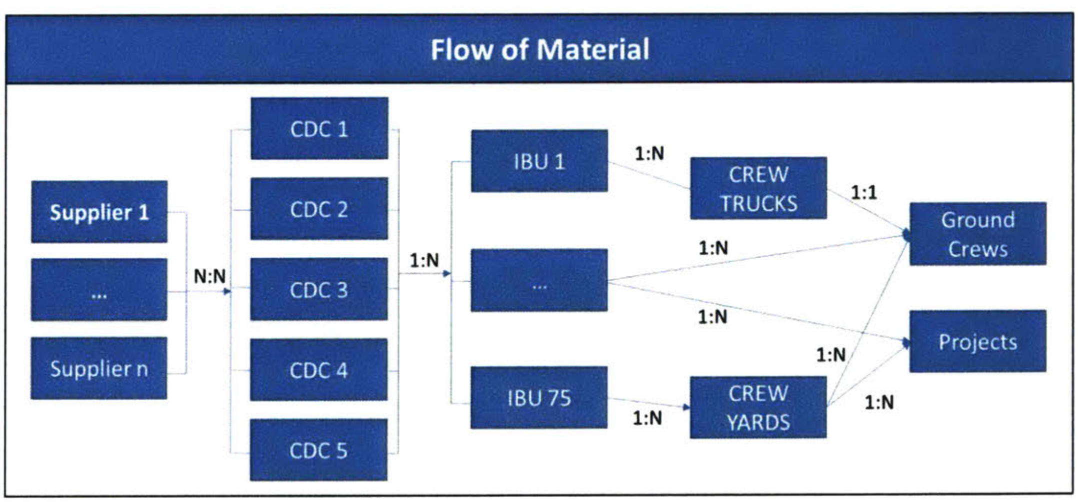


Figure 2-3 Supply Chain - Material Flow

2.3.3. Inventory Management

The Inventory Management (IM) Group is responsible for stocking the CDCs with the right material in the right quantity at the right time. One could presume that the distribution of KPIs, where 3/5 deal with financial and cost metrics, 1/5 deals with supplier control, and only one metric on the subject of service level, would be a good approximation to the priorities of the group. In fact, the service level is of highest priority, one could argue that by far.

Key Performance Indicators

The team's key performance indicators allow us an initial understanding of the supply chain priorities. One of the measurements of failure is tardiness, which is defined in the group by the number of days an order is not completely fulfilled beyond the supply chain's lead-time commitment - seven days. Equation 2-1 shows the calculation for order tardiness.

Equation 2-1: Tardiness - Days of unfulfilled demand

$$\mathrm{T}(d_t) = \sum_{j \in J} \sum_{T=t_s}^{t_f} \left(\tau_{d_{j,T}} - LT_{j,T} \right)$$

Where:

$d_{j,T}$: is a demand line in order *j* requested at t_s

τ : is the number of days order d has been pending fulfillment

$LT_{j,t}$: is the lead time for site j

Given the high cost of not meeting demand, the most important metric for the supply chain team is the service level. The Material Availability Ratio, or fill rate, is equivilant to service level and is defined as the ratio of orders that are delivered on time to the total number of orders, as depicted in Equation 2-2, including active materials only. On-time delivery is defined as an order where none of its items is tardy, in accordance with Error! Reference source not found.Equation 2-1.

Equation 2-2: Material Availability - Ratio of on-time to all orders

$$\mathrm{MA}(d_t) = \sum_{j \in J} \sum_{T=t_s}^{t_f} \frac{x_{d_{j,T}}}{d_{j,T}}$$

Where:

$d_{j,T}$	: is order j requested at time T
$x_{j,T}$	: is a binary element for order j at time T, $\mid \mathrm{T}(d_t) = 0 \Rightarrow x_{d_{j,T}} = 1$
τ	: is the number of days order d has been pending fulfillment
$LT_{j,t}$	: is the lead time for site j

Another metric central to inventory management is the inventory turns ratio, which shows the ratio between incoming inventories to outgoing inventory. This metric lets us know what is the average duration of inventory in the system until it is transferred to the regional operating companies. However, since the metric is based on value of inventory, it does so at a very high level.

Equation 2-3: Inventory Turns

$$Turns_{(t_f)}(t) = \frac{\sum_{T=t_s}^{t_f} V_{out,T,m}}{\frac{\sum_{T=t_s}^{t_f} V_{T,m}}{t_f - t_s}} \times \frac{t_f - t_s}{t}$$

Where:

$\frac{\sum_{T=t_s}^{t_f} V_{T,m}}{t_f - t_s}$	: Is average inventory value of material *m* held at period $t_f - t_s$
$\sum_{T=t_s}^{t_f} V_{out,T,m}$	: Is the total fulfilled value of material *m* for the period $t_f - t_s$
$\frac{t_f - t_s}{t}$	: Is the conversion term to transform to the desired interval, usually annual.

Two other KPIs, which we will not touch upon in this thesis are Supplier on Time Delivery, and Stranded Inventory Rate.

2.4. Key Insights

The challenges that the supply chain group face are significant and numerous.

Given the high underage cost, i.e., the cost of not fulfilling demand on time, the supply chain team is required to maintain a target service level of 99.1%. In fact, the service level achieved by the group frequently exceeds the target. However, since the service level is directly linked to costs and system control [5], it would imply either that the system is currently under tight control, or that the expenditures of the supply chain, as a whole, are high. One thing we know for sure is that with high underage cost and low material degradation rate, incentivizes material overstock.

However, in order to have a high level of control, it is necessary to have visibility deep into the demand process. Appropriate information systems need to be in place [6] to allow seamless end-to-end monitoring and controlling. As we previously discussed, although there are information systems in place as well as digital connectors to bridge between systems, the information passed is entails significant noise. Therefore, it could be inferred that the levels of inventory held are very possibly higher than needed in case demand and supply under control.

Additionally, buffers and delays in information transfer, such that occur when material is needed in the field, which goes through the IBU store keeper to be ordered, then through several systems until it reaches the CDCs and suppliers, are known to cause a bullwhip effect in inventory. Furthermore, lead times, batch ordering, and any intermediary inventory between the manufacturer and the actual demand, cause a bullwhip effect as well.

Informational barriers, legacy policies and procedures, and cultural averseness to change compound these challenges. Since each operating company continues to work, at least in some part, using legacy policies and procedures, documentation of material usage and resource planning is carried out differently across the company. For example, although there are company wide standards and procedures installation procedures and material may vary from region to region. This has surfaced in a previous attempt to create a demand forecast that is based on combining project outlook with company work standards. The results concluded in over-purchasing material that is rarely used while under-purchasing necessary material.

In this chapter, we discussed the company and analyze it using the three organizational perspectives. Additionally, we further describe the supply chain organization, the flow of information and material, key metrics, challenges, and drivers of performance.

Chapter 3. Literature Review

As presented in the approach section of the introduction, the goal of this paper is comprised of two efforts. The first effort is oriented to improve the productiveness of material demand with a noisy signal, using data mining techniques and machine learning. The second effort is oriented to quantifying the effects of changes, such as improved forecasting.

We present in this chapter three sections, each with an overview of a separate field of study. In the he first section, we discuss phenomena and challenges in supply chains. We evaluate the effects and causes of the bullwhip effect, in addition we discuss different methods to account for supply chain performance.

In Section 3.2, we discuss demand forecasting in the past and present. Before detailing the different methods in which machine learning is applied to improve forecasting, we briefly discuss a similar problem in the field of market segmentation. Although, there are some fundamental differences between the two problems, there are also a great number of similarities in the problem and the solution. We then present a discussion on the application of unsupervised clustering, and time series analysis.

Section 3.3, focuses on network simulation. In addition to presenting some of the methods, tools, and technique that are used, we touch on a network model architecture that is suited for quickly scaling models for large supply chains.

3.1. Supply Chain

In order to understand what to measurements we need to account for, we first need to define what a supply chain is, after which we can identify what the indicators and drivers of a high performing Supply Chain are.

3.1.1. Definition and Key Concepts

The definition of a supply chain varies throughout the literature in accordance to the type of supply chain, scale, industry, application, and objectives. This phenomena is extensive enough that the Council of Supply Chain Management Professionals (CSCMP) notes in its own definition of supply chain, that the subject includes a broad range of schoolings and applications that the there is no exact clear definition. However, it is widely accepted that supply chain generally entails a network of entities working to transfer products, information, services, or finances through a system [7].

3.1.2. Bullwhip effect

The bullwhip effect, or Forrester effect, is a phenomina where the observed demand changes in respect to the distance the observer is from the actuall demand. Meaning that as you move upstream from the point of consumption, the observed demand signal will incorporate additional noise [8] in the form of increased demand variance. This is experienced as sharp and volitile swings in demand that increase with every incorporated delay in material movement or information transfer.

To illistrate, lets observe the operations of a local pharmacy a week before a marathon takes place neer by. If there is a lag of information, and the pharmacist is not aware of the marathon or its implications, he could persive the additional demand for anti-chaff cream as a growing trend and increase its order for the item. However, after observing a drastic drop in demand after the race, the pharmasist realized his error but is now stuck with a storeroom full of anti-chaff cream. Now if we take a step upstream and observe the supplier who is also unaware of the race, his drastic rise in demand from unrelated stores around the city and the drastic drop in demand the week after will be the aggregation of all the stores compounding the magnitude of the effect.

In practice, this also happens in a supply chain that is entierly comprised of a single supplier and a single demand source at each stage. Chen *et al.* in their 2000 paper [9] identify that at any stage of the supply chain, if theres is either any error between forecast prediction and actuall demand, or any change in the perseption of the mean or variance of demand, will create a bulwhip effect. Furthermore, material lead times, invenroy, batch sizing orders, missalignment between Information Systems and human bias, are all sources for the bulwhip effect. This is especially evident where there is inventory at the point-of-use, as in our case.

In addition to operational causes there are also behavioral causes for the bulwhip effect. Behaviors such as lack of communication and collaboration, misstrust between parties [10], decentralized control and planning [5], are central to the propegation of the effect. Furthermore, behavioral aspects may maintain the bulwhip effect even in cases where the necessary steps are taken to eliminate it. For example, in an environment where there is not a comlpete trust between the coordinating parties may still create a bulwhip effect even though there is an effort to collaborate, as well as the proper systems and processes. If one party is not 100% confident that her counterpart will do exactly as they planned, either because she is not sure the communication was clear or perhaps she belives there is a greater risk to error on the down side, it is plausible that she will diviate from the plant suppressing the effects of the collaboration.

There are methods to mitigate the bullwhip effect. Building trust, collaboration, and communication are important however, IT is key. Unimpeded information transfer is necessary, from the point of use scanner to the final supplier. Building on these two foundations, processes such as Just-In-Time, Vendor Managed Inventory, Sales and Operations Planning can significantly reduce the bullwhip effect.

3.1.3. Inventory

Additional insight could be drawn from [11] on his classification of inventory. Willems identifies ten different stock types, seven of which have relevance to the utility supply chain and are detailed below.

I) **Cycle stock**

Inventory held to meet regular demand. Cycle stock is usually a function of review frequencies or batching policies.

II) **Anticipatory stock**

Inventory held to satisfy an exceptional demand that it itself is a binary event. For example, inventory procured in light of an expected storm.

III) **Obsolete Stock**

Inventory that conforms to all GAAP and FASB rules as active inventory, although practically there is no chance that it will be used.

IV) **Pipeline stock**

Inventory moving through the supply chain.

V) **Safety stock**

Inventory held to buffer against every type of variability in the supply chain.

VI) **Pre-build stock**

Advance accumulation of inventory to meet demand, due to capacity constraints. For instance, inventory build-up before winter season.

VII) **Early Arrival stock**

Inventory that arrived earlier than expected.

3.1.4. Key Metrics

To understand the drivers of a supply chain; let us assess what is a well-performing supply chain. Whitten et al. propose a definition of supply chain performance as the ability to "provide products and services of appropriate quality in specific quantities and at the appointed time", in addition to the ability to minimize the total cost of the service or product to the final customer [12]. Zhang and Okoroafo [13], add that in addition to delivering the right product, at the right place, at the right time, a performing supply chain will do so at the lowest cost of logistics. The authors continue to define basic considerations for performance:

Efficacy: Achieving predefined objectives;

Efficiency: Achieving results without waste; and

Effectiveness: Satisfaction with the results

Further perspective can be taken from the widely accepted SCOR framework, as well as the scorecard developed by [14] designed for a regulated utility. The SCOR framework, emphasizes the performance attributes reliability, responsiveness, agility, costs, and asset management efficiency. While Yoder proposes delivery performance and turn metrics (see Figure 2-1) for the supply chain, SCOR adds an additional level of consideration in measuring encompassing metrics such as, Total Cost to Serve, Cash-to-Cash Cycle Time, Return on Supply Chain Fixed Assets and Return on Working Capital.

Table 3-1: Yoder 2013 Proposed Supply Chain Scorecard

Inventory Management FY2012 - Scorecard Layout 2012						
Measure	Performance Previous FY	Comments	Performance	Previous Month	Dash Board	2015 Goal
Project/Program Performance to Plan	N/A	Reported as FY Projects/FY Cancelled/FY Delayed/FY Ahead of Schedule (Preliminary Engineering - Construction)	619 / 1 / 231 / 101	N/A	↓	N/A
CDC Par/Free Order Fill Rate	N/A	Reported as the percentage of STORMS and MSR Orders that are filled completely	77.3%	N/A	↑	95.0%
CDC Par/Free Line Fill Rate	N/A	Reported as the percentage of total units filled for all MSR and STORMS orders	87.3%	N/A	↑	98.0%
Inactive Material	N/A	Reported as the inventory value of material that has no activity since 2010	13.85%	N/A	↔	1%
Net Discounts Claimed	N/A	Percentage of invoices successfully processed with discounts against all invoices processed with discounts available.	85%	N/A	↑	90%
Cycle Stock Inventory Turns	N/A	Reported as the inventory turns for all inventory materials excluding emergency stock	1.65	N/A	↓	2.35
Total Stock Inventory Turns	N/A	Reported as the inventory turns for all inventoy material including emergency stock	1.37	N/A	↑	1.82
On Time PO Receipts	N/A	Reported as the percentage of POs arriving on or prior to the due date for FY2012	60.7%	N/A	↑	81%
On Time POs with 7 day grace period	N/A	Reported as the percentage of POs arriving less than 7 days after due date for FY 2012	77.0%	N/A	↔	85%
Total Inventory Value	N/A	Total value of inventory including emergency stock	$ 121,561,894	N/A	↔	$ 91,659,894

3.2. Demand Forecasting

In the absence of complete certainty, i.e. true stationarity, forecasting aligns the business with the behavior of the outside world. For most businesses, the goal is to keep the least amount of inventory needed to satisfy demand, and thus minimizing associated costs. However, the costs of not holding enough inventory and not perfectly conforming to demand may include reduced capacity utilization, increased expediting costs lost sales, etc. [15]. The use of demand forecasting, therefore, is to allow the service provider to prepare the resources necessary to supply their service at a target service level [16], while minimizing errors.

The use of demand forecasting is widespread and is implemented using a wide range of methods. Simplistic methods of demand forecasting can include the usage a priori knowledge, while more advanced and rigorous methods will use external attributes, historical data or a combination of the methods.

demand forecast, however, does have its downsides. One example is that the usage of demand forecasting is based on the assumption that there is a sufficient quantity of reliable data, whether it is from previous experience or historical data. Without a clear transfer of reliable data and information throughout the value chain, the capabilities for forecasting, planning, and, optimizing are limited [17]. Another issue is that the use of any forecasting method that is not perfect and does not assume a constant mean and variance to the demand, increases the variability of demand and exacerbates the effect of bullwhip down the supply chain. [9]

Although humans perform well identifying charted trends with a limited number of variables [18]. However, with the increase of dimensions, data points, or other complexities, such as time lags, their ability quickly diminishes [19]. Furthermore, using visual inspection to identify trends over a large number of items may become a daunting, time-consuming task.

In our context, identifying different project types according to their demand profile, when the number of instances (projects) and the number of dimensions (materials used) are limited, is a simple task, well in the realms of human performance. However, in order to group a sparse matrix that includes a large number of instances with numerous dimensions into similar project types we turn to study a similar problem.

Segmenting models have evolved with time and technology. Initial segmentation, mainly based on a priori knowledge, was found to be inherently biased by the nature of the analyst. Further elaboration identified key attributes, such as sex, marriage, age, or education level to attempt and describe the customers' expected behavior. Introducing standardization to the key attributes model, descriptive attribute segmentation transformed the key attributes to numeric variables allowing the performance of additional quantitative and statistical analyses.

The attribute-based models rest on the assumption that the recognized attributes actually represent difference in demand behavior. Alternatively, recent segmentation models, including Statistical feature and behavioral model segmentation, use historical consumption data. Statistical feature segmentation uses a combination of calculations, weighting and statistical transformations performed on historic data to reflect customer behavior. Several drawbacks arise from the methodology [8]:

I) There are no algorithm or rules to which one could design or replicate models
II) The process is more art than science
III) Highly dependent on the knowledge and capabilities of the analyst

3.2.1. Market segmentation, a similar problem

Market segmentation assumes that a heterogeneous market consists of smaller homogeneous markets with differing product preferences [20]. The process of market segmentation divides potential customers into groups according to similar features. Further research supported market segmentation by demonstrating that applying forecasting to smaller, and more homogenous, groups produces more accurate results due to an averaging effect on errors [21].

Similar to our problem, market segmentation is regularly done based on a large number of instances and products. Initial research recognized the importance of reducing the number of identified outcomes, i.e. market segments, to a limited number when the number of instances is large .

Behavior model segmentation relies on the existence of patterns, in the historical data, that can be useful to predict future behavior. Several issues occur with this model:

I) Existence of patterns
II) Noise occurring from measurement error, bullwhip or other may obscure such patterns

III) Existence of historical data, i.e. past interactions.

3.2.2. Machine Learning

Although current forecasting and segmentation models produce robust results, they remain to be hypothesis-based experimentations. In other words, the baseline and any improvement on a model is only possible in the case the analyst correctly hypothesizes variables that successfully describe the differing factors. One aspect of machine learning is the ability to identify describing signals that humans would otherwise not discover.

Most machine learning techniques follow the following sequential steps: Data-preprocessing, data discovery, model training and model validation. We discuss some of these steps in the next section.

Preprocessing

Data pre-processing may be one of the most important steps of machine learning. Often the data collected include out of range values, impossibilities, missing data, etc. Failing to adequately process the data prior to training or feeding the model can lead to failure to converge, increase in processing power and time needed, or false outputs. The process of preprocessing includes cleaning, instance selection, normalization, transformation, feature extraction and selection, data preparation.

Noise in data is almost unavoidable. Furthermore, model performance may be heavily influenced by the quality of the input, therefore, models must be robust against noise of the learner. The classifications of noise are defined as Class noise, i.e. the mislabeling of instances, and attribute noise, which includes erroneous attribute values, missing or unknown attribute values, and incomplete attributes or values that are irrelevant to the question at hand. The literature describes several approaches to deal with noise including Robust learners, Data polishing methods, and noise filters.

Furthermore, using different data types or units may also skew results. In many cases a defined model or algorithm is designed to use and combine several sources of information in order to get the intended results. The compatibility of these data is essential to attain results that are reliable. For example, identifying what are the key influencing variables for electric poles and nuts, where the former us measured in batches while the latter is measured in units, can perhaps increase the significance of poles, more than would be deemed reliable, or may even obscure the results all together. In order to assure compatibility of the different items, scaling and shifting are used. One example of such method is data normalization.

Another challenge for machine learning is high dimensionality. Bellman 1961 [22], defines the "Curse of dimensionality" identifying that the any increase in dimensions increases the sample space exponentially. Several methods are available to reduce the dimensions of a dataset, including filtering, selecting and creating features, as well as other types of supervised or unsupervised transformations.

One method for dimensionality reduction is the Singular Value Decomposition (SVD). SVD uses linear transformation to create a low rank approximation of the original dataset matrix. It does so by factorizing the original matrix into three matrices: $M = U\Sigma V^T$, where M is the original data, the columns of U and V^t are orthonormal and Σ is a diagonal matrix with non-negative real numbers.

3.2.3. Clustering and Partitional Clustering

In the literature, we find many types of clustering techniques. For this review, we will discuss Partitional Methods, and Hierarchical Clustering, the objective of which, is to find underlying patterns and stuctures in data by identifying groups that are homogeneous internally but hetrogenouse extenrally. [23]

Partitioning methods subdivide the data into a pre-specified number of clusters - k. These methods can be either centroid based, clustering around a gravity center, or medoid based, clustering upon the average internal dissimilarity. [24]

It is generally accepted that K-means is one of the highly used partitional clustering methods, due to its simplicity and performance with large datasets.

Lloyd's Algorithm [25]:

Let there be a set X, with a distance$d: X \times X \rightarrow \mathbb{R}_{+}$, and an output of a set $C = \{c_1, \dots, c_k\}$

Find a set C of k clusters that fulfill the following:

Equation Error! No text of specified style in document.: Lloyd's Algorithm - cluster identification

$$\min \sum_{\chi \in \mathrm{X}} d(\phi_c(x), x)^2$$

1) **Chooses the initial centroids**

   most basic method being to choose k samples from the dataset X
2) **Initialization - placing centroids**

   K-means has shown susceptibility to bad initialization. Using k-means++ algorithm for initialization, k-means is guaranteed to find a solution that is O(log k) competitive to the optimal k-means solution [26]
3) loop to until difference between iterations is less than threshold
   a. Assigns each sample to its nearest centroid.
   b. Create new centroids by taking the mean value of all of the samples assigned to each previous centroid.
   c. Compute difference between the old and the new centroids

Additional variations to the objective function:

K-center: $\min max_{\chi \in \mathrm{X}}\, d\ (\phi_c(x), x)$

K-median: $\min \sum_{\chi \in \mathrm{X}} d(\phi_c(x), x)$ [27]

There are several known issues with the algorithm. First and foremost, the algorithm takes as an input the number of cluster it is searching for in the data. This implies that the user needs to know how many clusters there are prior to running the algorithm. Additionally, the performance of the algorithm may change in accordance to the location the it initializes the search for the centroids. For instance, if the algorithm initializes the centroids near a local optimum the centroid may remain there. Moreover, distributions that are not Gaussian may be problematic to identify. Additional issues include, possible susceptibility to outliers [28], and susceptibility to identifying no data or outliers as clusters.

Hierarchical Clustering

Hierarchical clustering takes an incremental approach to map the distances between instances, usually displayed using a dendrogram.

Agglomerative Algorithm

The algorithm builds clusters starting with individual instances, iteratively pairing close instances, and finishing with one cluster.

Let there be a set X, with a distance$d: X \times X \rightarrow \mathbb{R}_+$

I) Create x clusters, each with one object
II) Iterated until there is only one cluster:
    - Find the closest pair of clusters and join it.
    - Update the distance matrix for the newly created cluster

Divisive Algorithm

Starting with one initial cluster, dividing chosen clusters, based on predefined criteria, into k clusters with each iteration, until we reach the state where the number of clusters equals the number of instances, each accounted within one of the clusters.

Defining Proximity Between Clusters

I) **Single Link or Min:**
   Proximity between the closest two instances in different clusters.
II) **Complete Link or Max:**
   Proximity between the two farthest instances from two clusters.

III) **Group Average:**

Average pairwise proximity between all pairs of points from different clusters.

IV) **Ward's Method:**

Proximity defined as the increase in squared error of merging two clusters.

V) **Centroid:**

Proximity defined as the between the centroids of two clusters.

VI) **The Lance-Williams Formula for Cluster Proximity**

Table 3-2 Table of lance-Williams Coefficients for common hierarchical clustering approaches.

Clustering Method	$\alpha_{\mathbf{A}}$	$\alpha_{\mathbf{B}}$	β	γ
Single Link	$1/2$	$1/2$	0	$-1/2$
Complete Link	$1/2$	$1/2$	0	$1/2$
Group Average	$\frac{m_A}{m_A+m_B}$	$\frac{m_B}{m_A+m_B}$	0	0
Centroid	$\frac{m_A}{m_A+m_B}$	$\frac{m_B}{m_A+m_B}$	$\frac{-m_A m_B}{(m_A+m_B)^2}$	0
Ward's	$\frac{m_A+m_Q}{m_A+m_B+m_Q}$	$\frac{m_B+m_Q}{m_A+m_B+m_Q}$	$\frac{-m_Q}{m_A+m_B+m_Q}$	0

Any method that can be represented with the Lance-Williams equation, here below, it's calculations can be represented be a series of decisions making the need to keep iterations of proximity matrices redundant.

Equation 3-1: Lanc-Williams Equation

$$p(R, Q) = \alpha_A p(A, Q) + \alpha_B p(B, Q) + \beta p(A, B) + \gamma |p(A, Q) - p(B, Q)|$$

Although hierarchical clustering is often an elegant method of decomposing variance, it is very expensive in terms of computational and memory requirements. This is especially problematic for noisy and high dimensional data. Furthermore, the algorithm does not attempt to achieve a globally optimal solution. In fact, it does not even have an objective function. On the contrary, it algorithm attempts to achieve a the locally optimal solution at every step.

Measurements of Similarity

In order to measure the validity of a given cluster we want to both minimize heterogeneity within the clusters, which is the mean value of all pairwise distances between all elements within the same cluster. In addition, we want to minimize homogeneity between clusters, which is the mean distance of all pairs of elements a_i and b_i where a_i belongs to A and b_i belongs to B. In other words, we want instances that make up a cluster to be as similar as possible to one another, while having instances in different clusters vary from one another as much as possible.

There are many ways to test for the above metrics as well as to measure the distance. Here below we detail two primary methods.

I) First, **Weighted Mean Absolute Percentage Error** is robust and efficient, considered a go-to in statistics.

Equation 3-2: Weighted Mean Absolute Percentage Error

$$M = \frac{1}{\mathrm{n}}\sum_{j=1}^{k}\left|\frac{y_j - \hat{y}_j}{y_j}\right| \times W_j$$

II) **Silhouette coefficient** combines the measurement of homogeneity within the cluster with the heterogeneity between clusters into one number.

i. For the i_{th} object, calculate its average distance to all other objects in its cluster. Call this value a_i

ii. For the i_{th}object and any cluster not containing the object, calculate the object's average distance to all the objects in the given cluster. Find the minimum such value with respect to all cluster; call it b_i

iii. For the i_{th}object, the silhouette coefficient is:

Equation 3-3: Silsilhouette coefficient

$$s_i = \frac{b_i - a_i}{\max(b_i, a_i)}$$

3.2.4. Time series analysis, Regression and forecasting

Current Forecasting Method

The current forecasting method utilizes the built-in capabilities of the ERP software used by the company. A First-Order Exponential Smoothing Model is used [29] to consider seasonal variations. Here, the basic value and the seasonal index is calculated as shown in the following formulation [30]:

Equation 3-4 Exponential Smoothing

$$\hat{Y}_{t+i} = D_t \times S_{t-L+i}$$

Where:

Basic value: $$D_t = D_{t-1} + \alpha\left(\frac{V_t}{S_t} - D_{t-1}\right)$$

Seasonal Value: $$S_{t+L} = S_t + \gamma\left(\frac{V_t}{D_t} - S_t\right)$$

And:

$i = 12$	Forecast Horizon
$L = 52$	Period length
$\hat{Y}_{t+i}$	Predicted demand for the period t+i
D_t	The current basic value for period t
V_t	Actual historical demand for period t
S_t	The seasonal index for the period t
S_{t-L}	The previous seasonal index for the period t

Now that we have laid the background for our proposed forecasting methodology, we will present in the next section the grounds for validating the results by simulating the supply chain network.

3.3. Network Simulation

Following the creation of the One of the benefits of simulation is the ability to model actual systems to improve the understanding of the drivers, through scenario experimentation, in addition to the capability to assess possible implications of changes to the system [2], [3].

3.3.1. Background to Simulation and Baseline Validation

In contrast to systems that need to be monitored over the continuum of time, such as simulation of weather systems, robotic movements, or rocket trajectory, supply chains may present extended durations of time with no change to the system. The graphical presentation of the variables we would want to monitor of the supply chain would, rather than a resemble a continues function, would resemble a step function triggered by discrete events within the model. Subsequently, simulating a supply chain using a continues time would be wasteful considering both time and computational resources. As a result, Discrete-Event Simulations (DES) are used to improve resource usage and allow the modeling of systems that would otherwise be too costly to simulate.

In DES there are three primary paradigms that are generally accepted – Activity-oriented, Event-oriented, and Process-oriented. The Activity-oriented paradigm, observes the occurrence of activities in increments of time. Breaking downtime into defined increments, the activity-oriented model would scan the all the different activities in the code to check whether an event is occurring. There are two possible drawbacks to this method. First, similarly to continues simulation activity-oriented may be prone to waste resources in the case that events occur only in a small portion of the increments of time resulting in a significant amount of the resources are used in scanning for events rather than processing changes in the system. Second, simulation outcomes may be significantly influenced by the decision on the duration of time increments in which the code checks the system.

The Event-oriented paradigm, improves on the Activity-oriented method, by creating a dynamic queue of expected events, and advance directly to the time of the next event. Thus, the event-oriented method is able to bypass the need to recheck all activities at each time interval. A significant proportion of time and processing, however, is used to find the next event or to sort the data structure by time of occurrence. The Process-oriented paradigm models sequential events as processes and utilizes uses parallel threads in the execution. Event though, n most cases, the libraries in the background work in an event-oriented mode, the process-oriented method is easier to write, as the creator of the simulation, as well as to read as an observer.

3.3.2. Relevant Formulas and Probability Distributions

Safety stock [31]

Safety stock		Lead Time	
		Constant	Variable
Demand	Constant	No Safety Stock	$R_L = R \times L$ $\sigma_L = \sqrt{R^2 \times s_L^2}$ $SS = F_S^{-1} \times (CSL) \times \sigma_L$
	Variable	$R_L = R \times L$ $\sigma_L = \sqrt{\sigma_R^2 \times L}$ $SS = F_S^{-1} \times (CSL) \times \sigma_L$	$R_L = R \times L$ $\sigma_L = \sqrt{\sigma_R^2 \times L + R^2 \times s_L^2}$ $SS = F_S^{-1} \times (CSL) \times \sigma_L$

Table 3: Safety Stock Formula

SS = Safety Stock

CSL = Service level

F_S^{-1} = inverse of the standard normal (Z)

R = Average Demand for Period

L = Average Lead Time for Period

R_L = Reorder Point

S_L = Standard Deviation Lead Time

σ = Standard Deviation of Demand per Period

Normal Distribution

The normal, or Gaussian, distribution is continues symmetrically distributed around a mean μ in proportionally to its standard deviation σ. Although it has its shortcoming, such as that it is continues throughout all real numbers and therefore it is possible, however improbable, to receive any number as an outcome, it is used ubiquitously in modeling.

Equation 3-5: Normal Probability Density Function

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

Poisson Distribution

The Poisson distribution is discrete and memoryless. It is often used to model arrivals or occurrences of events per interval of time, where λ is the average occurance per period.

Equation 3-6: Poisson Density Function

$$p(x) = \frac{\lambda^x}{x!} e^{-\lambda}$$

Exponential Distribution

If the Poisson describes the number of arrivals, let us say at a train station, in a certain interval of time, the Exponential distribution could be used to describe the time between the arrival of one passenger and the next. Often, but not always there is a direct relation between the Poisson and the Exponential distributions. As such, they can be described using similar parameter λ as the average occurrence per period time, or $\frac{1}{\lambda}$ as the expected time between two occurrences. [32]

Equation 3-7: Exponential Density Function

$$f(x) = -\lambda e^{-\lambda x}$$

3.4. Relevant Tools and Models

3.4.1. Python SimPy Simulation Library

SimPy is an open-source, process-oriented, discrete-event simulation library written with and for the programing language python. The SimPy library allows us to generate processes, such as inventory management, order execution, and demand generation, as well as resources, as inventory or machines. In addition, the library, takes advantage of existing Python attributes to cease and resume functions in mid-stream. This additional functionality, allows for a cleaner code and easier processing.

3.4.2. The Graves and Willem Model [33]

In 2000, Graves and Willems presented an architecture for a supply chain network model. In their work, they describe a single stage model, i.e. single node, with possible downstream demand and upstream supply. Each node is capable of holding inventory. Once implemented, the model is scalable by the simple propagation of the single node, allowing a simple and effective method of modeling large networks.

3.5. Key Insights

In this chapter, we reviewed the information, methods, and techniques that are used in the fields of supply chain, demand forecasting and machine learning, as well as network simulation.

Chapter 4. Demand Forecasting

To mitigate the effects of bullwhip observed by the internal supply chain team, the team needs to, first, improve visibility into the demand at point-of-use and then create a system-wide material plan, while collaborating with all the parties involved. Due to organizational challenges, discussed in Chapter 2, improving cross-company collaboration and visibility is not trivial from an organizational point of view. Therefore, to mitigate the bullwhip effect, reducing the number of unexpected orders in the short-term horizon, the team needs to rely on the improvement of internal capabilities and processes.

As discussed in Chapter 3, traditional demand forecasting is not only highly susceptible to the bullwhip effect, but also it may be a catalyst for it [6]. Furthermore, the efficacy of the forecasting model directly corresponds to the rank of transparency between the different tiers in the supply chain. The effects of these problems, as discussed in Chapter 2, make it problematic for the supply chain team to anticipate incoming orders in the short, month-by-month, term. In order to overcome these challenges, the supply chain team needs to have a better indication of the underlying demand source, the seasonality, and trends of different types of jobs and the material needed to complete these jobs. To do so attempt a new approach to forecast the demand.

In this chapter, we present the first part of our approach – uncovering underlying behavior patterns in the data. We start by describing the demand signal, how it is observed in the data, and what are the challenges associated with working with it. We continue by outlining the proposed approach, its rationale, and its implementation. We further describe the implementation of the first two steps of the process, as well as outlining the additional two steps, which will not be the focus of this thesis. Closing this chapter, we discuss our learnings conclusions from the work.

The evaluation portion of the thesis, quantifying the effects of improved forecasting, is provided in Chapter Chapter 5, where we discuss our approach to evaluating the efficacy of the proposed forecasting method.

4.1. Data - Sources, Description, and Challenges

Before we present the proposed methodology, we need to, first, understand the data that we are dealing with, its structure, its characteristics, and its challenges. In this section, we will describe the composition of the data, and the sources of noise within it. We further present in table Table 4-1 Types and Sources of Noise in the Data

The raw data format is a record of Stock Transfer Requests (STR) for material; each line event contains a Work Order Number; Date Stamp; Ordering Site Number; Suppling CDC Number; Material Number; and Quantity Ordered. The materials requested could be anything from nuts, and bolts, through concrete and poles, to wires and transformers. Similarly, the units in which the material is ordered could be gallons, pounds, feet, units, or packs.

For the purpose of this thesis, we shall define noise as any added or altered data that masks or changes the original demand signal, which is the actual usage of material in time and project association. We further classify types of noise within the data as Corrupted Data, User-Added Noise, System Added Noise, and Process Added Noise.

Despite our definition, we do not argue in this chapter for the dispensability of noise, one way or the other. In fact, It is plausible that there is a source of noise that is imperative to the optimal function of the system. For example, it could be that maintaining the supply chain's target service level is an impossibility without downstream inventory, which will necessarily add noise in the form of the bullwhip effect.

Noise in the data can derive from several possible sources:

4.1.1. System and Process Added Noise

One type of noise that can rarely be completely avoided is process added noise. In this case, the noise derives from the characteristics of the observed entity, i.e., projects, how it is carried out, and how the system is designed to support it. More than often, the causes for this noise are engrained in the culture, in the organizational processes, or in the nature of the work, making this type of noise difficult to avoid. One example is that the lifespan of a project, which can last as little as one day and as long as several years, can have a significant effect on the quantity and types of material used. A lengthy project may, perhaps, entail several smaller projects or perhaps it may have just been postponed to the next fiscal year. In each instance, it may fit into different sets of demand patterns.

4.1.2. User Added Noise

Users introduce noise to the data in two distinct ways – through human error and the introduction of mental biases. In order to request material, the end-users, such as downstream storage keepers; contract supervisors; and field personnel, need to manually input the necessary material and quantity needed for a project. The manual process gives way to erroneous inputs, which are predominant in the data, such as ordering the wrong material or entering the material number in the place of the needed quantity. The second type of noise introduced by users is the one that derives from the personal preferences, assumptions, and biases of the user as she makes the order. One situation, for instance, which has repeatedly been pointed out to in interviews, is that where crews and personnel hoard material "just in case." This has become predominant following a cross-company system malfunction, several years ago, that rendered the field crews with limited material support.

4.1.3. Information Systems and Technology Added Noise

Another source of noise occurs in the transfer of data between different information systems. As discussed in Section 2.3, the company's information systems portfolio is saturated with specialized applications, such as design and planning, power management, and other legacy systems that are connected to the company ERP. In addition to the communication challenges of data "translating" between one system and another, additional issues arise when the definition of the connectors are not perfectly aligned. These mismatches can appear in two primary ways. The first can take shape as a system material request without an actual need for that material. Furthermore, another case is with material requests that have been redacted in the origin system but not the company ERP. To illustrate, when an engineering design is complete, the design system outputs the materials and quantity needed for that work as a request to the ERP. However, the actual plans may be shelved until needed, frequently for several years.

Table 4-1 Types and Sources of Noise in the Data

	Description	Examples
System and Process Added Noise	Noise inherent in the process used to handle, send, receive or order material.	• Open warehouses • Downstream inventory • Changes in standard operating procedures that influence SKU usage on jobs • Material from different vendors may have different SKUs • Different unit measuring types • Lack of data labeling
User Added Noise	Erroneous or improper inputs entered manually by an end User.	• Mistakenly pressing several keys instead of one • Hoarding material at different levels increasing the bullwhip effect • Personal preference in working procedures
Information Systems and Technology Added Noise	Misrepresentation of data occurring in or by the transfer of data between different systems	• Cancelation in systems that do not migrate to the company ERP • System duplicate entries • Different order types
Corrupted Data	Data that is unintentionally altered in the DB when writing, reading, storage, transmission, or processing resulting in unusable datum.	• Can occur in the data transfer between different systems

4.2. Proposed Methodology – Part I

We propose an approach that improves forecasting by uncovering demand patterns underlying the observed demand, thus reducing the bullwhip effect. Without reliable point-of-use data or a fully integrated information system, we cannot attain reliable data on the true-demand to base a forecast on. Instead, we propose the use data mining techniques, as presented in Figure 4-1: Proposed Methodology, to identify underlying behavior patterns in the available data and, assuming that the pattern approximate the true-demand, create a forecast for material demand.

4.2.1. Data Preprocessing

In order to implement data mining techniques, we need first to prepare the data. The objectives of preprocessing the data are to conform the data to the algorithms that they will undergo, shorten duration and reduce computing power needed to train and run estimators, improve generalization of results, reduce chances of misleading results, and assure data integrity. We do so using the following process:

Subset Selection

The objective of subset selection is to reduce both the complexity of the data, by reducing the number of dimensions in the solution space, and the variance within the data, by simplifying the model and focusing on a small subset as possible. Two primary methods are feature selection, used filter out irrelevant features in the data, such as what group is responsible for procurement of the item, and instance selection. Similarly, instance selection is used to select a subset of the instances that are relevant to the question at hand, thus reducing irrelevant variance. For instance, each region in the company's service area may entail different technologies, procedures, and norms. By focusing on a single CDC, we improve the performance of the algorithm.

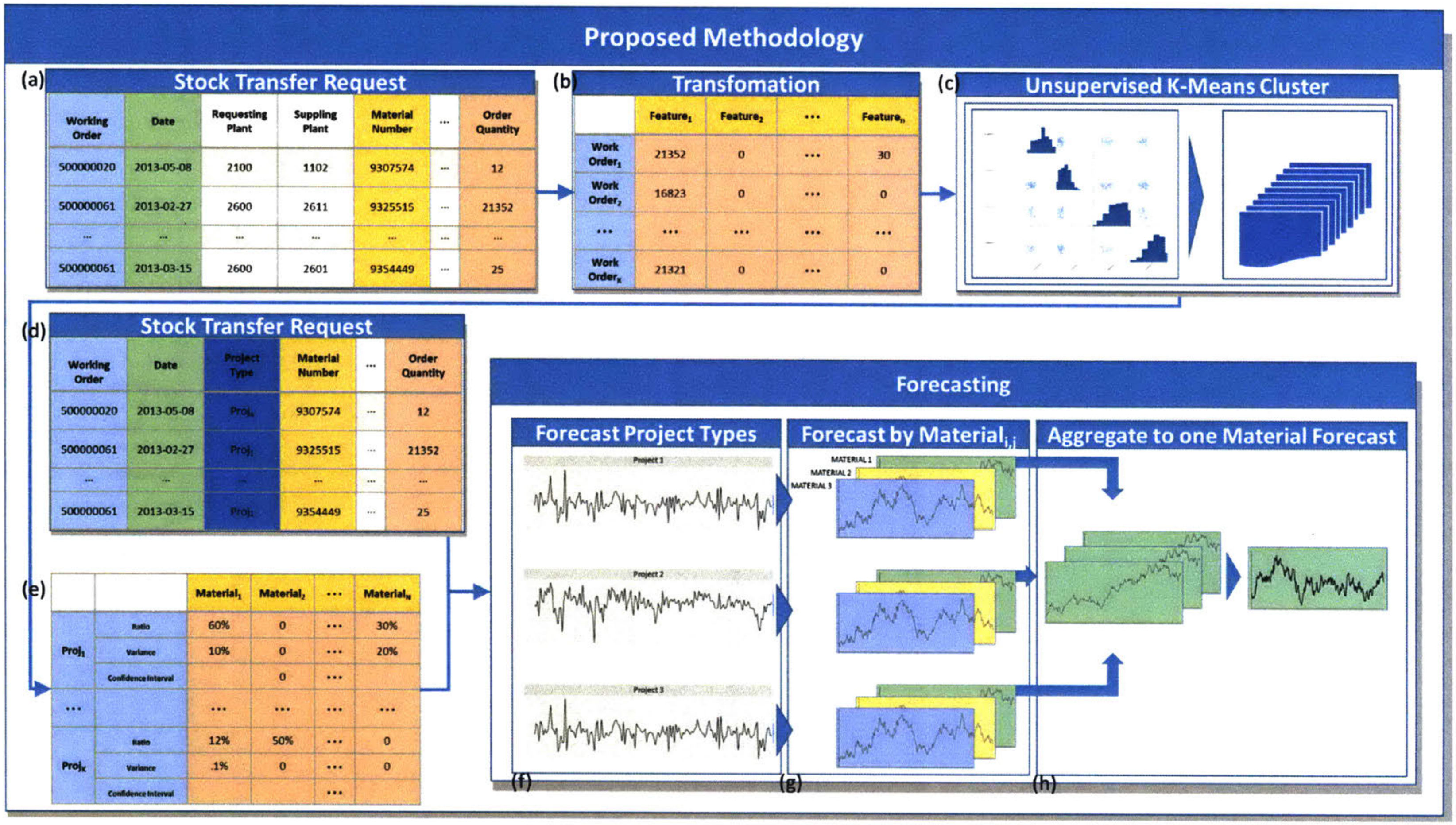


Figure 4-1: Proposed Methodology

For the purpose of this work, we narrowed the data to a single CDC and only for materials associated with electric projects. The filtered data set contained over 22 thousand work orders, each of which is considered a project, and over 1 million event lines, each line containing a single material number and quantity. i.e. average of just over 13 lines per Work Order. The data set is unlabeled, meaning that other than the Work Order number, and the association of the material to electric projects there is no indication of what type of project it is.

Data Cleaning

In the process of data cleaning, we identify unreliable data from the data set and subscribe the appropriate method of handling these exceptions. Two issues that are prevalent in data are logical errors and outlier instances. For example, errors in data recording can be found as a material number entered instead of quantity or other unreasonably large requests.

The issues that are found in the data are out of scale errors, such as orders with negative or extremely high quantities, and missing values. Orders with missing values are assumed to be corrupted data, in which the data is unreliable, or an erroneous input, in which case either the requester did not need the material or another order with a quantity will be resubmitted. In either case, these exceptions are removed. Negative values can either be an erroneous input or a material being returned to the CDC. To avoid the issue of labeling a returned item as an erroneous input, we eliminate negative instances only when the total quantity of material ordered by that project is negative.

Predominant in the data, instances with extremely high quantities are caused by several possible causes, such as an erroneous input, e.g., a material number is written instead of a quantity and addition of additional digits. Other legitimate causes can be a significant project, a contractor requesting all the material she will need for an entire season, and so forth. We identify these high-value exceptions by flagging all instances with quantities that are three sigmas over the mean quantity ordered for that material. Later, we remove all exceptions that the quantity is equal to a material number. The remainder of the exceptions are substituted with the average order quantity after the removal of these outliers were removed.

Structural and Data Transformations:

Differences in units of measurement, i.e., pounds; feet; units; packs, usage differences, i.e. the usage of cogs, in most cases, will be orders of magnitude higher than transformers, and magnitudes of projects are taken into account by scaling and shifting material quantities relative to the usage of each material. The data is scaled and shifted using the logistic function described in formula Error! Reference source not found.. Note that the final format of the data table will most likely be sparse. To avoid the issue of falsely accounting for the non-use of an item as a low use of an item, the scaling transformation is conducted on a material-by-material basis, and not in the cross-tabulated format with additional zeros.

Equation 4-1: Logistic Transformation

$$f(x_{i,j}) = \frac{L}{1 + e^{-k(x_{\mathrm{i,j}} - x_{\mathrm{0,j}})}}$$

Where:

L	=	100 (Arbitrarily chosen number)
e	=	Euler's Number
K	=	$\frac{1}{\sigma_j}$
$x_{i,j}$	=	The quantity of material j ordered for project i
$x_{0,j}$	=	The mean quantity ordered of material j

Before applying linear transformation and clustering, we transform the data into a cross-tabulated form. The transformation results are a matrix where rows represent projects or Work Orders, columns represent the Material Number, and the cross-section cells are the quantity of material ordered, as illustrated in Figure 4-1 b.

Lastly, we reduce the number of dimensions of the matrix, reducing the solution space and needed computational resources. The challenge with dimensionality reduction is that the process necessitates the loss of some descriptive information. Furthermore, many known and validated algorithms are unsuited to sparse matrices. For these reasons, we implement a linear transformation to the matrix using Singular-Value Decomposition (SVD). We use SVD to evaluate the retention of descriptive variance over a range of dimensions from 2 to 35, as shown in Figure 4-2. We use the elbow method, discussed in Section 3.2.3, to identify the appropriate number of dimensions. We reduce the dimensions of the matrix to 20, maintaining 99.7% of the explanatory variables. For the remainder of this thesis, we will refer to the extracted features, which are the results of the dimensionality reduction of the original features, i.e., Material Numbers, simply as features.

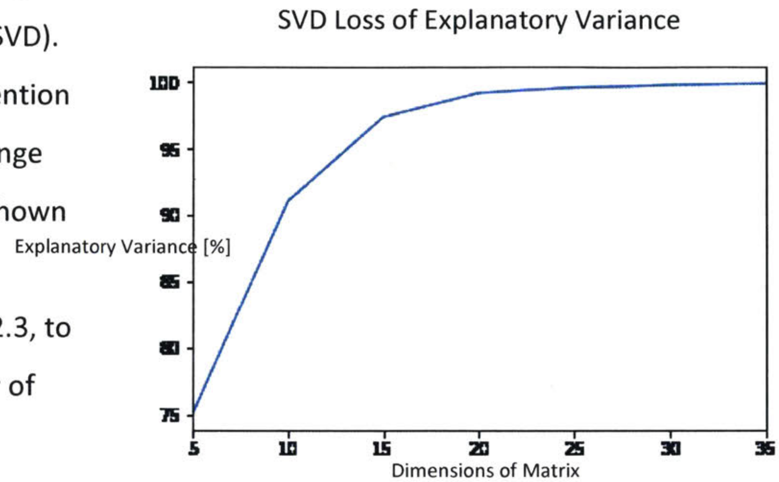


Figure 4-2: SVD - Loss of Explanatory Variance by Dimension

4.2.2. Demand Signal Segmentation and Evaluation

At this step, we uncover underlying behavior patterns as different material consumption profiles in the orders received from crew yards using clustering techniques. These consumption profiles generally represent different job types that are carried out in the field, though several of them would represent an all-inclusive bucket for noise, mixed projects, and one-off projects. Furthermore, the distribution of these projects throughout time can serve as a first approximation of the distribution of the actual demand. There are two underlying assumptions regarding the data at this stage. The first is that the raw data does, in fact, contains the information necessary to describe the actual demand. Second assumption is that the machine learning algorithm can distinguish between different profiles.

We conduct further analysis to evaluate and document the descriptive information of each uncovered consumption profiles. In the analysis, we create for each profile, an archetype along with the expectation, variance and significance levels for each material type within that archetype. The use of this information will be used to create the aggregated material demand forecast.

Separating Signal from Noise – Clustering

Following the completion of the preprocessing, we can start looking for underlying patterns and behaviors. To do this, we attempt to segment the demand signal into different project groups by implementing a clustering algorithm. Given that the data is not previously labeled and that previous attempts have failed in mapping and labeling these projects, we implement K-means, for its robustness with unsupervised clustering, as well as its substantiated efficiency with high dimensional and large data set.

The most challenging part in K-means Unsupervised Clustering is deciding on the number of clusters. To do this, we calculate the homogeneity within the clusters and the heterogeneity between the clusters using the Silhouette and Elbow methods, explained in Sections II) and Error! Reference source not found., respectively. A range, between 2 and 80, of different clusters, is tested and presented in Figure 4-3: Evaluation of Clusters for K in (2,80)

We find that in beyond K = 20, any increase in the number of clusters has a marginal benefit to the Silhouette performance. The clusters are evaluated in the edges of both extremes by examining both the distribution of instances between clusters and the demand profile of each cluster.

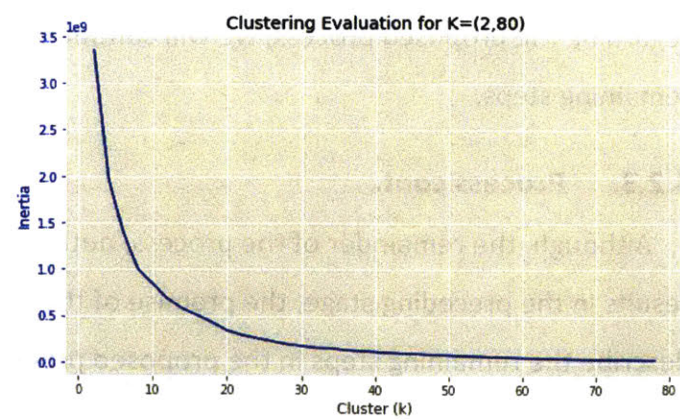


Figure 4-3: Evaluation of Clusters for K in (2,80)

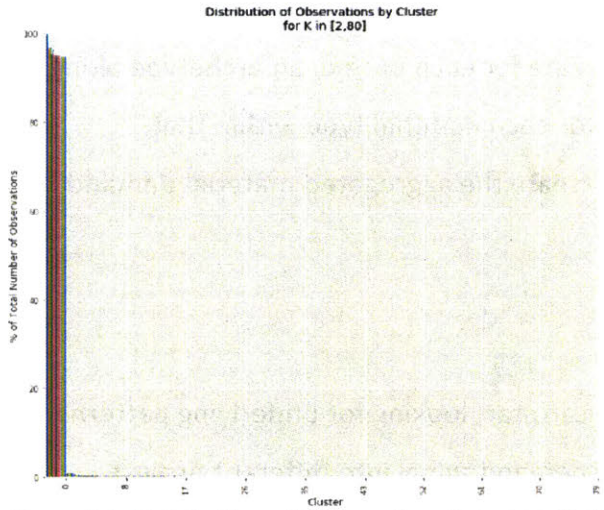


Figure 4-4: Distribution of Observations between Clusters over Different K

Interestingly, we find that the overwhelming majority of the instances are concentrated in a single cluster. In addition further analysis into the distribution of instances over a range of different number of clusters (K), teaches us that the results are unanimous throughout the complete range. As we see in Figure 4-4, for each number of K tested in the range of (2,80), an overwhelming proportion of the instances (>91%) is attributed to a single cluster.

Although the results do not provide us with sufficient signal classification to proceed with the rest of the model, they do not invalidate our premise that data mining techniques can uncover underlying consumption behaviors and that demand forecasting based these behaviors will produce superior results in decentralized controlled, multi-echelon supply chains.

We continue to discuss our findings, learnings and conclusions in Sections 4.3 and Error! Reference source not found., but, for the benefit of allowing the reader with continuity regarding the proposed process, we will continue with an outline and justification of the remaining steps.

4.2.3. Process cont.

Although, the remainder of the process, outlined below, has not tested, due to insufficient results in the preceding stage, the premise of the thesis is still valid. Therefore, we will describe the remaining steps in the proposed process for evaluation in future research.

2. Demand Signal Segmentation and Evaluation (Cont.)
   2.2. <u>Separating Signal from Noise – Clustering (Cont.)</u>

   Following the identification of the different [similar consumption profiles], we use subject matter experts to corroborate the accuracy of the clusters and the differentiation between them.

2.3. Create Project-Archetypes

For each project-archetype, we compute the expectation, confidence interval, and variance of the different material usage quantities within the cluster. We save the information for later usage as well as label the original data

3. Forecasting Consumption Behaviors

After identifying the significant consumption profiles, we undergo a time-series analysis and create a forecast for each archetype. The significance of this stage is the understanding of the seasonality, trends, and significance of each job type.

3.2. Data Preprocessing

Similarly to the previous preprocessing stage, here too, we need to conform the data to the algorithms that they will undergo. Using the same instances used in the previous stage, select the features relevant for time-series analysis: Work Order Number, Date, Project Type (Cluster).

For each project type, we create a time series to represent the frequency of projects throughout time. After splitting the data into training and test sets, we resample the data for monthly periods.

3.3. Forecast Model Creation

We now apply a time series analysis to each of the project groups. Although the specific model to be used is discretionary, and several models, such as Holt-Winters method or SARIMA, should be tested to optimize performance, the procedure for model creation are similar.

I) Create a baseline model for the data using a priori knowledge.
II) Evaluate model statistics: residuals, autocorrelation, partial-autocorrelation

I) Optimize hyper-parameters

II) Cross-validation using the test set

III) Evaluation

IV) Creating a Forecast

4. Material usage forecast aggregation

Once we have a forecast of the number of jobs, by type, that are predicted to occur at a given period, along with an assessment of the material types and quantities to be used for each job, we combine the two and reconcile the results into an aggregated demand forecast.

4.2. Demand Forecast for Material by Project

For each project, using the project-archetypes, we transform the project forecast into material forecast. In essence, we create for each project group as many demand forecasts as the number of material used by that project group.

4.3. Forecasts Reconciliation

It is generally inadvisable to aggregate individual forecasts directly since they rarely equal a high-level forecast. Alternatively, Hyndman, Lee, & Wang in their 2014 paper [34], offer a hierarchical aggregation approach to do such aggregation efficiently.

4.3. Discussion of Findings

As discussed in the previous section, the results achieved in the clustering stage have not met our expectations, and therefore we have not implemented the last two steps in the proposed process. The primary learnings, therefore, that we offer in this work is the identification of the causes for this mismatch and possible resolutions.

We identify two primary reasons for the curious distribution of instances between clusters, one data related the other algorithm related. As first introduced in the objective of the thesis, and later discussed in depth in Section 4.1.1, the magnitude of noise in the data is substantial.

The noise is primarily caused by point-of-use variation, such as personal preferences or project accounting norms; network-amplified variation, such as open-warehouse, downstream inventory; and inaccurate data, such as mismatches between different information systems.

The implications are that the data morphs extensively from actual demand to what is observed. It is plausible that the data in its current state is too scrambled to detect significant demand behaviors. Nevertheless, it is our opinion that this is not the case. A visual inspection of the relationships between the features indicates that clusters, patterns, and correlations do exist. In figures Figure 4-5: Material by Material Scatter Plots and Figure 4-5, we plot the purchasing of different material in units. Possible patterns are visible showing possible correlations in plots (2) and (5), possible groupings in (6) and Figure 4-6, as well as, perhaps, some of the challenges we face, such as susceptivity to outliers (1) and counting non-events (4). We can also see instances where the use of a particular material, practically excludes the use of another (3). Nonetheless, any improvement in data collection and management would substantially improve not only the performance of the proposed process but also the performance of the supply chain by simple process improvement.

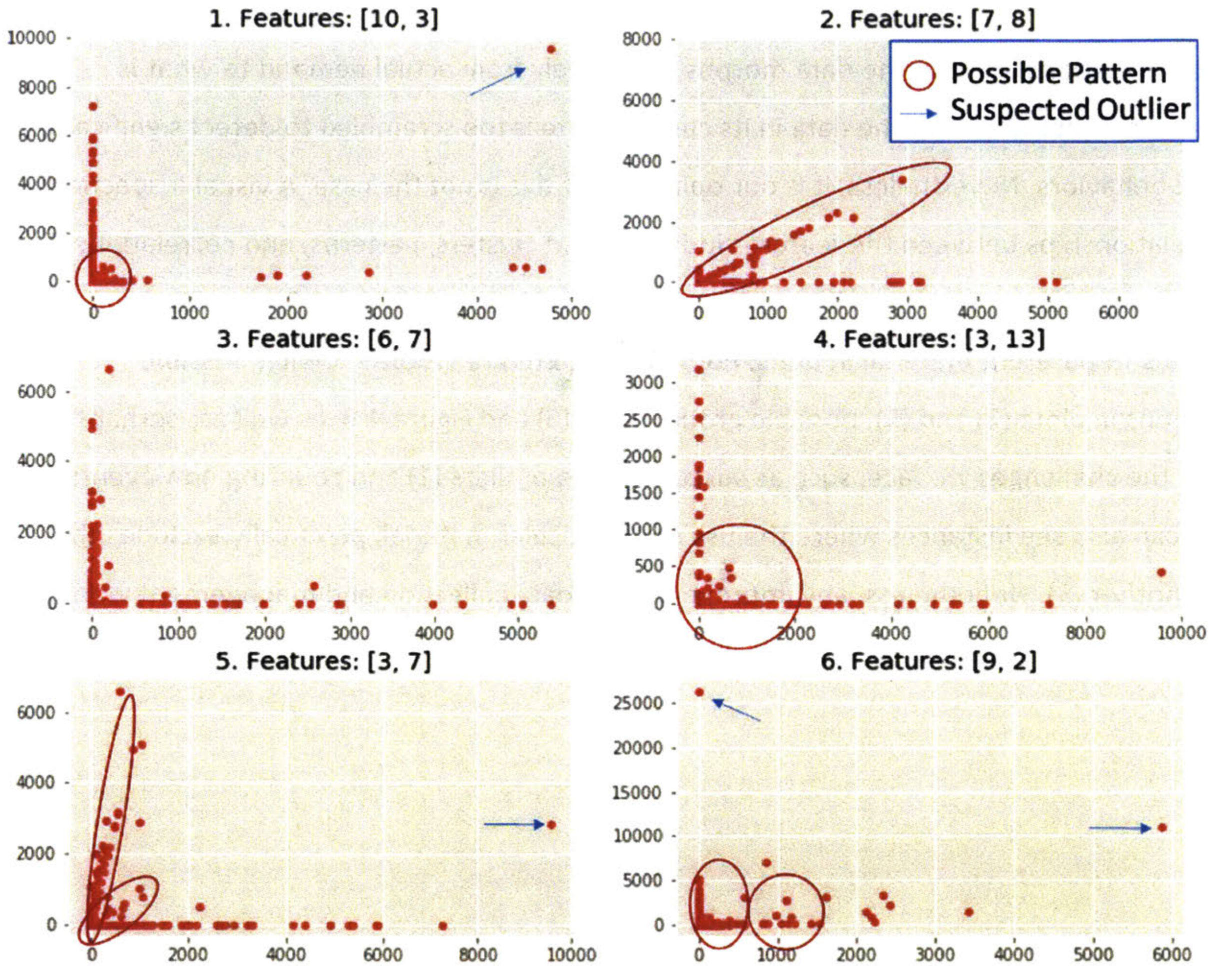


Figure 4-5: Material by Material Scatter Plots

An analysis of the density of instances for each feature, presented in Figure 4-7, shows that a significant portion of the instances is clustered around zero, i.e., no common usage. It is plausible that although the dimensionality reduction, or perhaps because of it, the sparsity of the matrix is masking the actual demand by imparting weight to non-events.

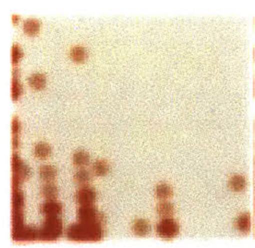


Figure 4-6: Material by Material Scatter Plot

Alternatively, it is possible that remaining outliers in the data set impair the performance of the K-means algorithm. As discussed in 3.2.3, the K-means algorithm may become susceptible to outliers when the outliers are distant enough from the rest of the data points such that the cumulative loss function, calculating the distance from the outlier to every other datum, overshadows the true clusters. The results are that the algorithm may identify a single datum as a cluster. However, it would be intuitive that given a high enough value of K, a subset of clusters would account for outliers while another subset would account for the true clusters. Nevertheless, in our case, as discussed in the previous paragraph, the results with K as high as 80 are comparable to those of K as low as two.

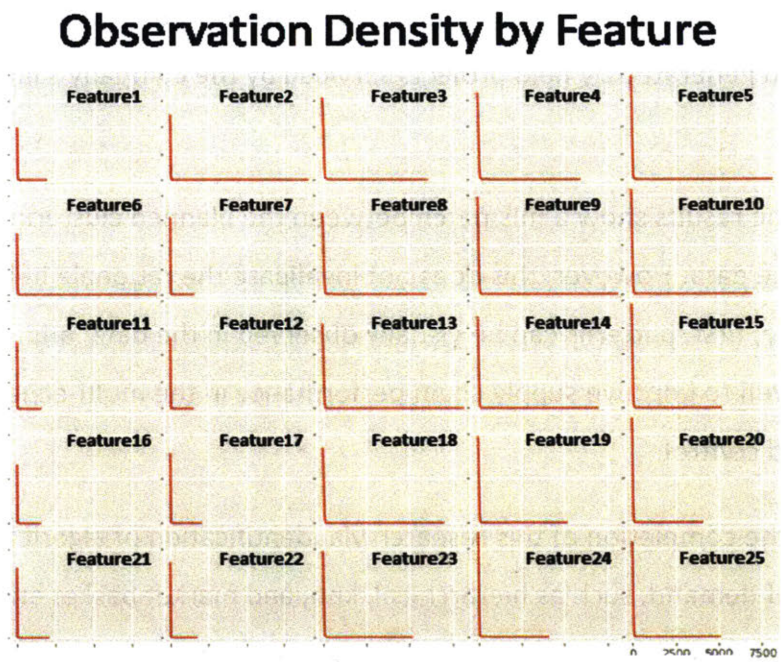


Figure 4-7: Observation Density by Feature

Another possibility is that the algorithm is incompatible with the data. The K-means algorithm was chosen due to its robustness with large data sets and performance with high dimensions. However, the algorithm works best when the distribution of data in the clusters is Gaussian (convex and spherical), which is not the case with our data. Furthermore, K-means is known to show limited performance in cases where there are clusters that are characterized by fuzzy boarders. The purchasing behavior between different material is partially linear and heteroscedastic at times, which is not optimal for the algorithm.

4.4. Key Insights

The use of digitization, automation, and IoT, to improve supply chain visibility, control, and performance, has been proven effective in supply chains around the world. However, organizations that this transformation is not a priority or do not have the resources to undergo it can still benefit from the subsequent technological improvements.

In this thesis, we propose a new approach to forecasting by migrating tools and techniques from the field of data mining to identify underlying behaviors that signify with greater accuracy the actual demand generated by field projects serviced by the company's internal supply chain team.

At this point, the results show a mismatch between the planned clustering process and the presentation of the data. However, this does not invalidate the rationale behind the proposed methodology since, first, patterns can be visually observed in the data, and, second, visibility to demand is proven to improve supply chain performance in the multi-echelon supply chain with decentralized control.

In addition to the completion of this research via identification of algorithms implementation of demand, such as hierarchical, knn, and market basket and validation of the remainder of the process. Future studies could expand on the subclassification of project elements throughout time, implication on material usage and the predictive significance of that information.

Chapter 5. Network Simulation

Evaluating effects of changes are difficult in large and complex supply chains. The implications of not knowing what will happen in the supply chain, in regards to risk and costs, can lead to bad decision making, proliferation of hidden issues, and aggregation of costs. The challenge in becomes especially difficult when there is limited visibility into the supply chain, such as cases where the supply chain is not centrally controlled, or where there are information issues or both. The results are that the costs associated with providing the customer with the material she needs are often hidden or obscured causing an inaccurate estimation.

Therefore, in order to evaluate the possible effects associated with implementing the novel demand forecasting methodology, described in the previous chapter, we present in this chapter an evaluation method using network simulation. We first give an overview of the objective, tools and scope of the model. We continue in presenting the design and relevant formulations of the model, followed by a depiction of modeling implementation. We conclude with presenting the findings of the simulation.

5.1. Overview

Supply chains are often driven towards complexity, through offshore sourcing, supplier diversification, multi-echelon inventory locations and more, with the objective of reducing costs and risks. However, supply chain complexity is making it increasingly difficult to accurately account for elements, such as costs and risks, associated with their operation, and to identify the drivers of these elements. It is often argued, that the total cost of a supply chain is directly correlated with the complexity of the supply chain [35]. Subsequently, it is ever more difficult to anticipate possible implications of decisions on the performance of the supply chain.

Furthermore, organizations that are prone to siloed behavior are inclined to exacerbate the issue. The information barriers, which reduce visibility between parts of the supply chain, not only increase the bullwhip effect within the system but also increase the risk of making decisions based on incorrect data. For example, a procurement decision to source an item offshore due to an enticing price advantage, without taking into account supply chain costs can possibly end up costing more than a higher priced option. It is reasonable to suggest that the cost of holding additional inventory at the CDCs, as well as the crew yards, and the repercussions of reduced confidence in the supply chain by the field personnel can overshadow any benefit attained by a price advantage.

To overcome this challenge we create a model of the end-to-end supply chain to evaluate the overall implications, regarding risks and costs. We further simulate different network designs to evaluate the cause and effects of issues, such as the bullwhip effect, as well as possible solutions.

5.1.1. Model Inputs and Outputs

The outputs of the model, shown in Figure 5-1 below, include three different items: sensitivity analyses, cost structures and KPIs, and IM decision history. The analyses output includes a dependency analysis between the different supply chain variables and a sensitivity analysis of the decision variables on total costs, as well as the department's KPIs, which include, Filtrate and Inventory Turns. We further save for future analysis the decision rules set by the simulation at each review point.

As inputs, the model takes several standard reports from the Enterprise Resource Planning portal, as well as financial and departmental information. The ERP reports, include Issuance\Receipt reports, from which we extract, the frequency of deliveries between nodes, as well as the arrival rate of requests for a given material by a given plant and the distribution of the size of the orders. In addition, we use the "Plant-Material" and "Material-Master" reports to populate the information on warehouse type of the node and material price and use.

We further input into the model, a distance matrix, budget information, and financial data, in order tp create the cost structure of the model.

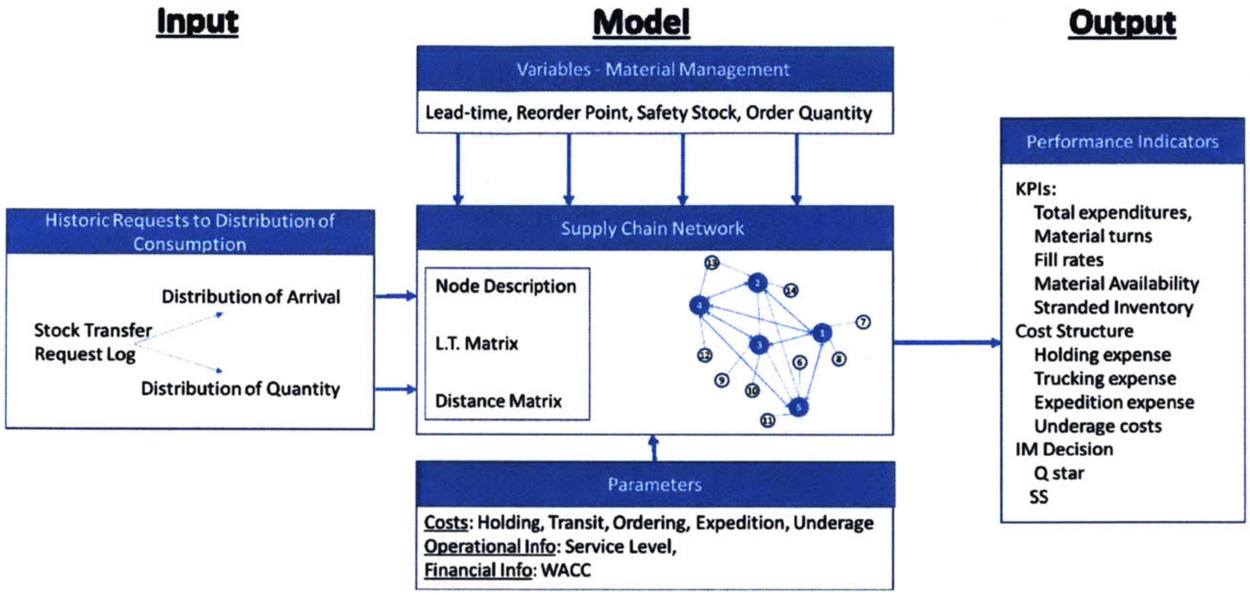


Figure 5-1: Model inputs and outputs

5.1.2. Assumptions

The objective of a simulation model is to evaluate a scenarios in such a way that is resource efficient in order to get better understanding of the system and its outcomes. An inherent part of the statement is the need to accurately model the desired system or the components relevant to attaining the desired information. An additional, and equally important, part is accurately placing processes to monitor the state of the system, its drivers, and its outcomes.

In the model creation, we build upon past and current research, instances, and interviews to emulate the modeled system. The model is therefore based on several assumptions.

First, inventory levels are known and maintained at each node of the supply chain. Furthermore, these levels are visible to the rest of the network and fully accessible by connecting nodes. For instance, a new order that cannot be fulfilled by the inventory at the node at which it was generated will trigger an inventory review process in all adjacent nodes. The node generating the demand will then be able to, subject to constraints, access the inventory of the neighboring nodes and replenish its own stock as well as satisfy the generated demand.

Second, recognizing the importance of maintaining a working power-grid, we assume that attaining the required service-level is of highest priority and therefore guaranteed. The implications of maintaining the required service level are double:

I) The target service-level is a requirement in both external and internal transactions
II) The organization is willing to pay a premium in order to guarantee the service level.

The third assumption is that the supplier is a source of infinite supply at a constant price. In point of fact, this assumption does not hold over time, due to macroeconomic factors and natural events. Although there is merit for checking risk implications of supply shortages, the focus of this thesis is on predicting the behavior of the network in normal conditions. This aspect can be modeled in future research to improve the resilience of the supply chain.

We additionally assume that other than lead-time there are no additional order or material processing time either within the node or between nodes. In addition to network behavior internal factors, such as the capacity, utilization, and efficiency of warehouse employees or systems, and external factors, such as road condition, weather, and traffic, can influence the time it takes an order to arrive at its destination. For example, material arriving at a facility that is stocked overcapacity could remain in the inbound queue for weeks pending processing. Still we maintain the validity of this assumption since

i. Internode transfers, in most cases, do not spend more than a time-step in the simulation – in our case a day.
ii. Urgent orders are usually expedited through any inner-node processing.

5.1.3. Scope

The stocks used for the simulation were chosen on account of their significant annual throughput value, as well as their prevalence in the network. The items consist of material used for the construction, maintenance and repair of the electric distribution network; they include: cable, wires, clamps, and crossarms.

The network model consist of three tiers of nodes connected through arcs. The three tiers consists of a consumption tier, representing the crew yards or IBUs, a intermediary tier, representing the CDCs, and a supply tier. The nodes in the consumption tier both generate demand and hold inventory. Furthermore, they are able to request supply from either nodes in the intermediary tier or other nodes in the consumption tier.

Nodes that represent the CDCs hold inventory and supply nodes in the consumption tier, as well as other CDCs. Unlike the consumption tier, the nodes in intermediary tier are also able to request supplies from the single node in the supplier tier. The supplier node, supplies all the nodes in the intermediary tier. Under the assumption that there is no supply shortage, on the supplier side, the supplier node acts as a supply generator not bounded by a capacity limitation, and therefore acts as an infinite source.

We narrow the scope of the modeled network to include all the CDCs, IBUs and a single supplier, summing up to 45 nodes.

5.2. Methodology

Creating a network model that adequately emulates a supply chain is not trivial. To simplify the problem we break it down into two subjects – a network problems and an inventory problem. The network problem encompasses the graph challenge - accounting for the nodes, arches, and weights networks, and identifying the correct fulfillment route. The inventory problem accounts for the policies, priorities, cost structure of the network. We solve these problems following the methodology we detail in this section, summarized in the steps here below.

I) Identify Supply Chain Parameters, Variables, and Objective Function
II) Map Supply Chain Network

III) Model build

IV) Model validation using a deterministic process

V) Evaluation of forecasting methodology using a stochastic process

5.2.1. Identify Supply Chain Parameters, Variables, and Objective Function

Accurately modeling a supply chain necessitates a clear understanding of the different drivers influencing the supply chain. Following the identification of the main drivers, we map the organization's priorities and subsequently create the objective function used by the IM team.

5.2.2. Map Supply Chain Network

The second part of the problem is the mapping of the supply chain. Given that the network consists of over 40 primary nodes, including CDCs and IBUs, and additional crew locations and designations in excess of 70 nodes, we use the historical material receipts and issuance log to calculate the frequency transactions between pairs of nodes. The result is a delivery frequency matrix, where each pairwise relation accounts for an arch between two nodes.

In addition, we use the location of the warehouse in the log to create a distance matrix using Google Distance Matrix API. Similarly to the frequency matrix, which is used to create the arches between nodes and add weight to the arches as Lead Time, the distance matrix is used to add a cost weight to each arch. The underlying assumption is that the company encures a transit cost that is in direct proportion to the driving distance between the nodes. Although, in fact, the distribution routes may group several nodes into one route thus significantly reducing the number of miles driven, we argue that this is probably done in similar proportions between nodes.

5.2.3. Build Model

In order to evaluate possible effects to supply chain performance, we create a network model to emulate the supply chain network. Given the general characteristics of supply chains and particular characteristics of the products supplied, we use SimPy, a Python based library, to implement a discrete-event simulation (DES).

We first implement the simulation in two modes: deterministic and stochastic. We initialize all runs with a warm up run time of 800 days. The models run for a duration of 1824 days, since there is five years of data.

5.2.4. Deterministic - Model validation

First, in order to validate the model we run the simulation using historic request and compare the decision made by the model, and its performance, with those of the supply chain.

5.2.5. Stochastic – Evaluation

Next step implementing a stochastic process, we simulate the effects widely accepted methods and phenomena that influence supply chain performance, such as pooling inventory across CDCs and extending supplier lead times, and evaluate if the results align with our expectations.

Finally, we simulate the forecasting methodology presented in Chapter 4. Although we do not have sufficient results to complete the forecasting section of this thesis, we are able to demonstrate the evaluation capabilities of the model by simulating an improvement to the forecast error.

5.3. Model Design and Formulation

The model follows a simplistic model design proposed by Graves and Willems [33]. This design provides the model scalability so it may fit any supply chain network using basic supply chain information and a single constructor. The basic elements of our model are:

I. A simulation environment designed to keep track of time, metrics, common data, as well as a general node directory.

II. A single node, representing an inventory holding location, , representing an inventory holding location,, representing an inventory holding location, designed to store descriptive information as well as to monitor and maintain inventory information.

III. Two arches – a downstream arch for demand fulfillment, and an upstream arch for replenishment management.

The scalability of the design lies with the combination of the latter two elements.

Let us denote V_{n} as the set of nodes n comprising the scaled supply chain network, and $v_{k,c} \in V_n$ as a node, such that $k \in \{1,2, \dots, n\}$ and $c \in \{consumption,\ \text{intermediary}, supplier\}$. At scale, each of the nodes $v_{k,c}$ is connected to n' additional nodes, each through a shared directional arc $E_{i,j}$, where $i \in v_{k,c}$ signifies the upstream node and $j \in v_{k,c}$ the downstream node. Although an ordered path of material originates at the supplier node, passes through a single intermediary node, and then to a consumption node where a demand was generated, to reduce lead times and allow pooling material may pass through a longer path between the supply node and the consumption node.

The exogenous demand generated at the consumption nodes, may be modeled either a deterministic or a stochastic fashion. When the demand variable is stochastic, the internal demand, as well the solution space, which include the set of nodes and arcs required effectively fulfill demand, also become variant in nature. However, processes such as lead times, will remain deterministic regardless. Once node *j* initiates a request to node *i*, the inventory is allocated to node j and is appropriated after a preset lead-time.

To incorporate this parameter in the decision-making process we calculate a first order approximation of the degree of activeness of an arc using actual transaction history. The activity of arch E is signified by $\phi_p \omega E_{i,j}$ where ϕ_p represents the number of transfers during period p.

Equation 5-1: Activity rank of an arch

$$\gamma_{i,j} = \frac{\sum \phi_p E_{\,i,j}}{p}$$

Where

$$p = t - t_0$$

Through the above calculation, we receive the frequency of deliveries from node i to node j for a given period p. Furthermore, we can present the inverse of the calculation as the average time between deliveries, between node i and node j. The lead-time for internal transactions is set as:

Equation 5-2: Expected lead-time between nodes

$$LT_{i,j} = \frac{1}{7 \times \gamma_{i,j}} = \frac{p}{7 \times \sum \phi_p E_{i,j}}$$

Furthermore, the lead-times for supplier transactions remain deterministic.

5.3.1. Parameters and Variables

The team's key performance indicators allow us an initial understanding of the supply chain priorities. we incorporate these indicators into the model.

A central factor in policy decisions is the cost associated with the material. These cost are varied and may amount to a substantial sum. Nonetheless, they are rarely evaluated as a whole in decision-making processes. Such costs can include procurement, ordering, transporting, holding, handling and more. In our model, we focus on the following cost drivers: Holding Cost, redistribution costs, expedition costs, as well as the cost of Service level:

Equation 5-3: Cost drivers

$$TC = \sum_p I \times C_{holding} + \sum_p \omega \times C_{transshipment} + \sum_p \theta \times C_{expedition} + \sum_p L \times C_{tardiness}$$

We calculate holding costs of material m at warehouse j by dividing the annual budget of a warehouse, which includes the WACC of holding the inventory, by the weighted proportion of the space taken by a material, multiplied by the average inventory $\bar{I}_m$ held at that location.

Or:

Equation 5-4: Holding Cost calculation

$$C_{holding} = \frac{Annual\ Warehouse\ Budget}{\frac{Loc_{m\in j}}{Loc_j} \times Loc_i(val) \times \frac{\bar{I}_m}{Loc_i}} = \frac{Total\ Warehouse\ Costs}{\sum \frac{Storage_t \times \overline{(stock)_{\iota,t}}}{\frac{storage_t}{\sum_t storage_t}}}$$

The redistribution costs are calculated using standards industry rates for full-load truck shipment. Since these costs are based on the driving distance, and the number of combinatory combinations of distance between nodes grows exponentially with the number of nodes, or by $\frac{n(n-1)}{2}$, we categorized the warehouses into 3 groups: a set of pairwise nodes sets for which the distance is known, a set of nodes that are central to other nodes, and a set of nodes that serve distant nodes. Note that the sets are not necessarily mutually exclusive.

To calculate the distance of the latter two categories, a stochastic process is assigned, using an exponential and normal distribution, respectively. We denote the accumulated distance traveled as $\omega\phi_p E_A$, where ω signifies the accumulated distance traveled at period p between nodes in subset $A \subset V_n$.

Expedition costs, are premiums occurred while acquiring material from external source. The premiums may be due to higher prices from vendors not supplying in bulk, approving and using alternative vendors, or shortening lead-times.

Material expedition is also used to manage the preassigned service level in the following manner: a customer places an order at a consumption node. If the material is available at the node or available for redistribution at adjacent nodes, the customer will receive his order on or before seven days pass. Similar to the critical fractile method, the material expedition process samples a normal distribution such that $P\left(\mathrm{Z} \leq \frac{\mathrm{x}-\mu}{\sigma}\right) = SL$, where x is the lead-time defined to the customer. The demand fulfilment process seen by the customer is therefore:

$$Min(\ Standard\ Supply\ Process\ , max(Lead\_Time, Materail\ Expedition))$$

Lastly, the cost of not meeting demand. For different industries, the cost of not meeting demand may vary. For a candy shop, not having a customer's favorite candy may necessitate the customer to pick a different item or to walk away. In the utility industry, however, the implications of a ground crew not having the material they need for their job could be much more than a lost sale. We define L as the number of days a customer awaits her order past the defined lead-time.

5.3.2. Objective Function

Further inquiry into the cost structure of operating the supply chain provides us with the following objective function:

Equation 5-5: Objective Function

$$\min\left(\sum_{T=t_S}^{t_f}\left(P_m Q_{m,T} + \sum_{i,j\in A}\phi_{i,j,t}C_{tran} + \sum_{j\in k}K_{j,t}C_{order} + Q_{m,j,T}C_{Hold} + \psi_{j,T}C_{Exp}\right)\right)$$

Where:

$P_m Q_{m,t}$	: Price of material m, times purchased quantity Q at time t
$\phi_{i,j}C_{tran}$	: Cost of redistribution ϕ from node i to node j
$K_j C_{order}$	: Cost of placing an order K from the supplier to node j
$Q_{m,T}C_{Hold}$	: Cost of holding Q amount of material *m* at node *j* for time *t*
$\psi_j C_{Exp}$	: Costs of Expedition ψ from node *j* at time *T*

5.3.3. Fulfillment

The objective of the supply chain, and the simulation, is to fulfill the demand generated by crews in the field. To supply the needed material to the field, we implement two different processes for regular stock fulfillment. The first process, described in detail in 0, fulfills the demand generated by customers at consumption nodes. It does so by identifying the optimal path to fulfill a demand generated by a consumption node and places the necessary orders. The second process 0, manages the inventory levels at each stock location, i.e. each node.

Demand Fulfillment

Let us define $K(d_{j,t}) = \{v_0 v_1 \dots v_k | v_i \subset V_n\}$ as the set of arcs connecting the consumption node j to the optimal set of nodes to fulfill demand $d_{j,t} \in \langle D_{j,t}\rangle$ subject to the policies and constraints of the supply chain. In a deterministic scenario, the sequence and magnitude of elements of $\langle D_{j,t} \rangle$ do not change and, therefore, K too could be presented as a sequence of non-changing elements. However, when demand is generated through a stochastic process, for different iterations $K_{d_{j,t}}$ no longer consists of the same elements, which increases simulation and computational complexity.

To overcome this complexity we implement two algorithms, a variant of the branch and bound algorithm for customer order fulfillment, and a variant for minimum spanning tree for inventory management. For information on algorithms, please refer to [36].

The fulfillment algorithm's objective is to identify a fulfillment path that emulates the optimal path according to the behavior of a material planner. The algorithm, maps the shortest supply path to a CDC, which it assumes as it's parent CDC, and labels it as it's escalation path. Afterwards, for each incoming demand, the algorithms runs a branch and bound algorithm for each echelon. After exhausting the inventory pool of the sub-network, the algorithm escalates the search to sub-network of the next echelon. Once enough material is identifyied to satisfy demand, the algorithm checks what is the minimum number of nodes that could fulfill demand, minimizing transit costs.

(1) Start with demand d_{v_0}at node v_0

(2) Create an empty set $K_{j,t} \subseteq K(d_{j,t})$

(3) $v_j = v_0$

(4) Create an empty set $V_{path}(v_{0,j})$

(5) Find path to CDC, while minimizing total lead time

(a) Create a set of all nodes adjacent to $v_j, N(v_j)$

(b) If v_j is CDC, add to and return:

$LT_i = 0$

$\omega_i = 0$

$V_{path}(v_{0,CDC}) = v_j$

(c) for $v_i \in N(v_j)$; do:

(i) $LT_i = LT_{i,CDC} + LT_{j,i}$

(ii) $\omega_i = \omega_{i,CDC} + \omega_{j,i}$

(iii) $v_j = v_i$

(iv) repeat step **(5)**

(d) add argmin(LT_i) to $P(v_{j,CDC})$ and return: LT_i, ω_i, $V_{path}(v_{j,CDC})$

(6) Add $V_{path}(v_{0,CDC})$ to $K_{j,t}$

(7) V_j = first node in V_{path}

(8) Create an empty set $V_{queue}(v_i)$

(9) Create an empty set $V_{checked}(v_i)$

(10) Escalate Branch and Bound

(a) if $Q_t\left(K_{j,t} \cup V_{checked}(v_i)\right) \geq d_{v_0,t}$ do:

(i) find the set$V_k = \{V_k \subseteq V_{checked} | K_{j,t} \cup V_k = d_{v_0,t}\}$

(ii) add V_k to $K_{j,t}$

(iii) Create orders for nodes in $K_{j,t}$

(iv) end

(b) Create a set of all nodes adjacent to v_j, $N(v_j) = \{\ v_u \backslash V_{checked} \cup K_{j,t} | v_u\ such\ that\ v_{i,j}\}$ and

(c) add to queue / update queue

(d) Update all neighboring nodes with elements + self

(e) If $V_{queue} = \emptyset$

(i) If $V_{path} = \emptyset$: end

(ii) Next node in $V_{path} \backslash V_{checked}$

(iii) Repeat step 10

(f) Sort V_{queue} according to LT

(g) $v_j = V_{queue}$next element in

(h) Repeat step 10

In effect, the algorithm creates several sets of nodes or paths, $K'(d_{j,t})$ that could together satisfy the customer-generated demand.

We now define the expected time it would take to fulfill demand $d_{j,t}$,

Equation 5-6: Lead time from nodes in set K for demand j,t

$$LT_{j,k}K(d_{j,t}) = \max_{K' \in K}(\sum LT_{j,i}(v_j v_i) \; \forall \; v \,|\, vu \in E(K'))$$

as well as the material demand seen by node i due to demand $d_{j,t}$

$$\mathrm{d_{j,i}} = \left(\mathrm{d_j} - Q(K_{i-1,j,t}(d_{j,t})\right)$$

Stock Keeping

While the previous process identified the optimal set of nodes to fulfill demand, there is still the necessity to assure that the right nodes have the right amount of inventory at the right time. Maintaining the right amount of stock levels is crucial to meet both regular and unexpected demand.

Let us define three types of pairwise relationships between nodes: parent-child relationship; neighbor relationship; and indirect relationship. We define the parent-child relationship as a relationship where the parent node is responsible for the fulfillment of the child node. The feature becomes relevant when, for instance, demand from a child is not fully fulfilled by the system, the parent node maintains the residual demand $\varphi_{j,i}$as a backlog. The relationship between neighboring nodes we define as connection where the nodes can request material from and obtain supply from, but are not responsible and do not maintain an account of any unfulfilled demand. The last relationship is between a node and the set of nodes that do not have an arch connecting between them. However, although these nodes are not directly connected, they may still be effect one another by a intermediary node.

At any time t, v_i can observe demand from three sources: customer generated demand at v_j, where $v_i \in K(d_{j,t})$, denoted as $\mathrm{d_{j,i}}$; demand forecast $F_{\mathrm{i,t^*}}$, where $\mathrm{t}^* = t + forecast\ time\ horizon - response\ time$; and the residual unfulfilled demand of a child node $\varphi_{i,u,t}$. We will represent this aggregated demand simply as $d'_{i,t}$.

Finally, let us define internal node variables and parameters.

$RoP_{i,t}(D, LT, SS)$ – Reorder Point. Recalculated every 30 days as a function of demand, lead time, and safety stock

$I_{i,t}$ – Inventory level for v_i at time t

$PS_{i,t}$ – Pipeline stock for v_i at time t

Q_{Sys} – Order quantity as defined by system (ERP)

$Q^\star$ – Optimal ordering quantity based on EOQ

$Exp\_Ratio(\phi_{i,j,t})$ – $\phi_{i,j,t}C_{tran}/\psi_{j,T}C_{Exp}$

For node j

When $I_{j,t} - d'_{j,t^\star} \leq RoP$

(1) Set demand $for\ v_j$: $d_{v_j} = \max(Q_{Sys},\ Q^\star,\ RoP_{j,t} - I_{j,t} + d'_{j,t^\star} - PS_{i,t})$

(2) Create a set of all nodes adjacent to $v_j, N(v_j)$

(3) Find $v_i \in N(v_j)$ such that $\min LT_{j,i}(v_i v_j)\ |v_i v_j \in E(v_j)$

(4) Set as parent node and request d_{v_j}

(5) If $LT_{j,k}K(d_{j,t})$ >t *

(a) if $Exp\ Ratio(\phi_{i,j,t}) < 1$, expedite

(i) Request $\min\left(d_{v_j}, Q_t(v_i)\right)\ \forall v_i \in N(v_j)$

(ii) Update residual demand at parent node

5.3.4. Fitting Distributions

A significant element in the modeling process is identifying an appropriate distribution for the different stochastic elements. This task has become simpler, and accessible to the public, with the proliferation of open source scientific packages [37] and software. The challenge not to over-fit, however, remains. In Figure 5-2 we show how different distributions map against the distribution of item quantity in orders.

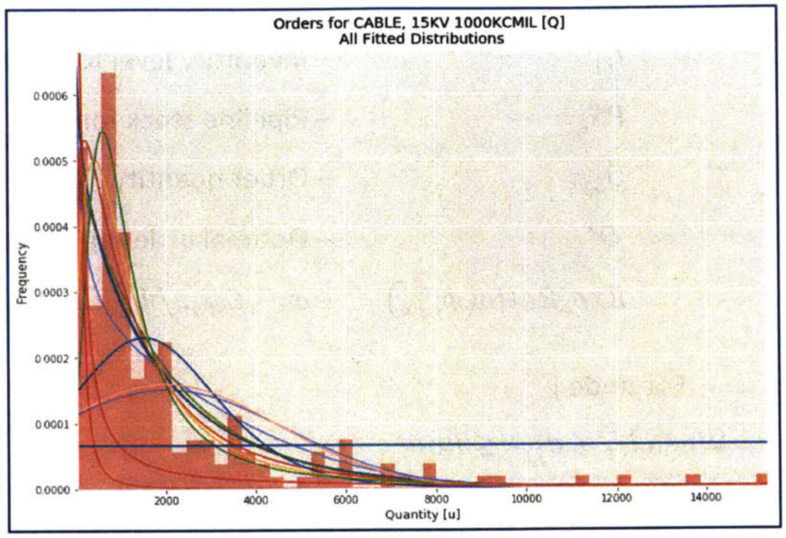


Figure 5-2: Order quantity plotted against different distributions

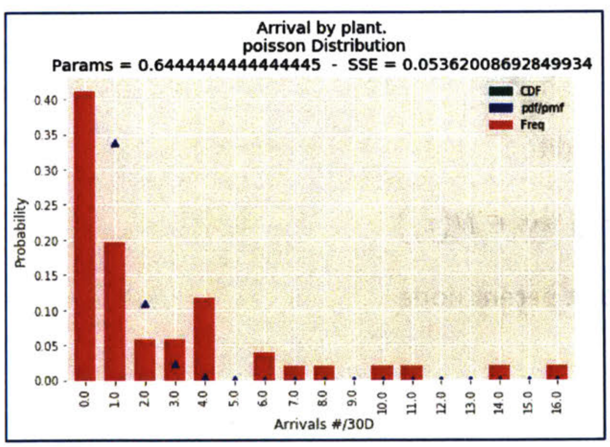


Figure 5-3: Show of fit - arrival against the Poisson distribution

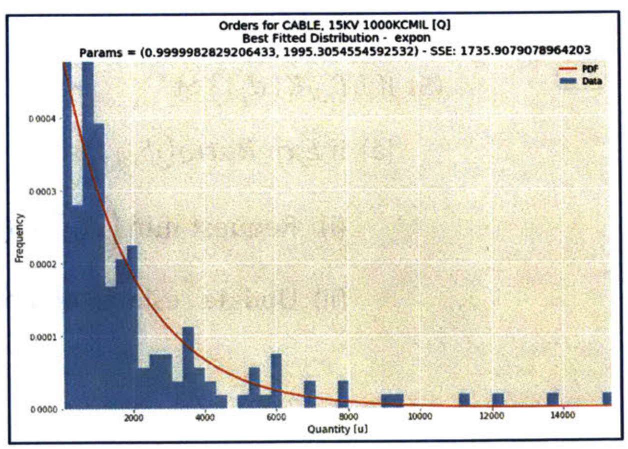


Figure 5-4: Show of fit - order quantity against the Exponential distribution

For simplification purposes and to avoid overfitting, in this thesis we implemented the stochastic processes using the standard distributions for each process. The two primary processes, the arrival rate of orders and the quantity of material for each order, are modeled using the Poisson distribution, presented in Figure 5-3, and the Exponential distribution, presented in Figure 5-4, respectively.

5.3.5. Design of Simulations

The objective of the simulation is to act as a evaluation tool for the proposed forecasting methodology. The underlying assumption is that supply chains are often too complex to accurately assess the impact and implications of change initiatives. Once we are able to create a representative model of the supply chain we are able to evaluate different scenarios, effects, and even possible counter measures.

In the following sub-section, we will present the variables we altered to achieve the conditions that will emulate the scenario in question. In addition to validating the effects of forecasting, we model several additional scenarios, including the resourcing material offshore and increasing demand.

The implications of the offshoring scenarios are extended lead-times and an increase in inherent normal variability. Unlike variability from political and macroeconomic factors, though pertinent are not the focus of this study, the inherent variability refers to, for instance, a higher susceptibility to weather conditions or an increase in opportunities for delays at a larger number of transfer gates, i.e. ship to ship or ship to truck.

Forecasting

In this thesis, we suggest a novel approach to demand forecasting. In this approach, we use data mining techniques to identify underlying patterns in the demand data, and base a predictive model on these patterns. Since the thesis focused on the first steps in creating the forecast model, there is no predicted data to feed into the model. However, because the validation portion is fundamental to the method, we implement the simulation on simulated data. We do this by implementing a sensitivity analysis to the theoretical performance of a forecasting model.

There are several methods to evaluate a forecasting model. In our evaluation we quantify the effectiveness of the model using the Mean Squared Error method, presented below in Error! Reference source not found.. To simulate the performance of the model we run a sensitivity analysis, where the an observation y_i is generated based on a predicted observation $\hat{y}$ along with a generated error that is normally distributed around the prediction with $\sigma = error$.

We discuss the results in 5.4.1.

Increased Supply Lead Time and Variance:

Supplier performance can have critical implications on internal operations. The extent of lead times, unpredictability in deliveries and constraints of supply can cause a company to hinder and fault, in some case, or even stop operations, in others. Simulating a possible scenario of transferring a supply source offshore, we test a range of both lead time and supply variances. We discuss the results in Section 5.4.2.

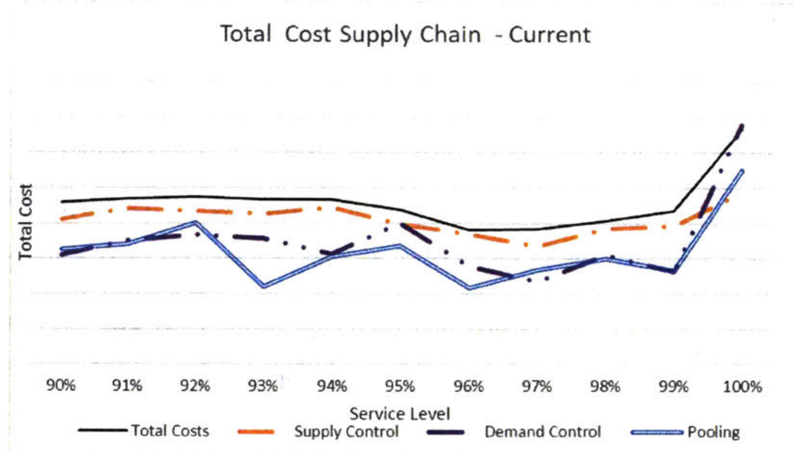
Increase in Demand Variability

The significance of increasing demand variability in the supply chain at utilities is not trivial. Aging networks, growing population, grid innovations and growing occurrences of extreme weather conditions, all induce additional stress on the already stressed system. We discuss the results in Section 5.4.3.

5.4. Discussion of Findings

The objective of simulation is to support decision making by exploring scenarios, evaluating dependencies, and testing assumptions, with minimal interference to operations, thus minimizing costs and risks. In this thesis, we use the simulation to model the supply chain network and evaluate the effects of improved forecasting on the system as a whole by measuring Total Costs, Reliability, Waiting Time, and Total Inventory.

However, before evaluating the different scenarios, we first evaluate the validity the model by comparing it against the actual supply chain in question. We compare between the KPIs of our model against the actual KPIs within the time span for which we have historical data.



We further evaluate the differences in inventory levels in both systems. The outputs we receive are within 3.2% of the observed values, meeting our requirements for model validity. In figure

We further use the base scenario as a baseline for further scenario testing. Here below are the outputs for the base scenario:

5.4.1. Forecasting

Understanding the implications of the forecasting performance on the complete supply chain, is crucial for the effective allocation of resources since the effects of improvements, by type and by magnitude, can impact the performance differently. It is plausible, for instance, that the error of a forecast with a time horizon of five days can be reduced significantly with limited resources. However, if the supply chain does not have sufficient time to respond to the forecast the results would be limited. Therefore, it is important to recognize what are the parameters that should be optimized.

In this thesis we perform a sensitivity analysis on the implications of forecast accuracy for one material with a time horizon of 14 days, which is equivalent to the supplier lead time of the material. We asses the impact on the costs and performance of the supply chain in reference to the validated baseline, as well as to additional independent variables. We initially expected to see an improvement in almost every performance metric - cost, turns, filtrates and number of expedited material.

Understandably, as presented in Figure 5-5, we observe an improvement of ~10% in the number of material expeditions; fill rates; and turns, respectively. However, we observe that there is only a limited impact on the holding costs in the supply chain. These results are counter-intuitive since knowing when and in what quantity an item would be needed should reduce the amount of material needed in the system. We believe that it may be attributed to the time horizon of the forecast, which was intentionally set to equal the lead-time for the material from the supplier but without including the internal lead times. Another explanation is that there is in fact a similar, or even more, inventory in the system but it is in the right locations, however, this would need to be addressed in future studies.

Figure 5-5: Change in material expedition against forecasting error

We further evaluate the effectiveness of the forecast relative to where in the supply chain it is generated and implemented. We find that at the level of the CDCs, the forecast significantly reduces holding expense but raises expedition expenses in a similar magnitude. It is important to note that the cost of expedition is significantly higher than the cost of inventory, leading us to conclude that, since the change in expense is similar, the amount of inventory in the system reduced drastically.

5.4.2. Increased Supply Lead Time and Variance:

In evaluating the effects of increased lead times, we find that inventory levels become the primary source of maintaining the desired service level. Although the objective of safety stock is to mitigate the variability in the supply chain, other processes such as order expedition, and redistribution, i.e. the transferal of material within a tier, are in place to help mitigate the risk of not having a needed item.

This differs from the baseline model, where expediting material could relief inventory capacity from the warehouses since lead time is one of factors for the expedition process. Although the effect was not completely intended for, in the modeling stage, this would be representative of material expedition in the new scenario since customs, expedition routes, and expedition timelines would make this process expensive and cumbersome.

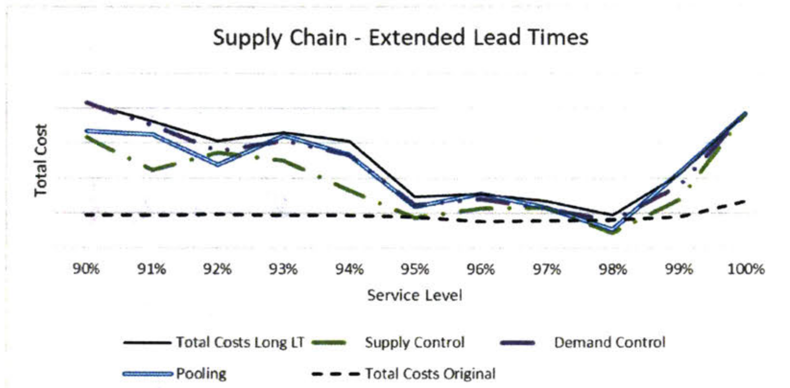


Figure 5-6: Supply Chain - Extended Lead Times

We identify a potential growth of between 150% and 300% in supply chain expense caused by additional holding costs expenses, expeditions expenses and stock-out costs. Additionally, we find that supplier management processes, i.e. reducing supply date variance, may reduce these additional expenses by as much as 22%.

In the case of sourcing material offshore we found that controlling for lead-time variance has the largest effect (22%), followed by pooling (17%), and then controlling for demand variance (8%). Although the results are somewhat intuitive regarding the first and third solutions, the second solution is not as intuitive since it is designed to mitigate demand variance rather than supply variance.

Generally offshoring material sourcing may have significant implications on a supply chain. In addition to the "normal" environment that we modeled parameters that were not factored in this model, such as macroeconomic and political events, foreseen outlier events as well as inevitable unforeseen events may increase the assessment significantly.

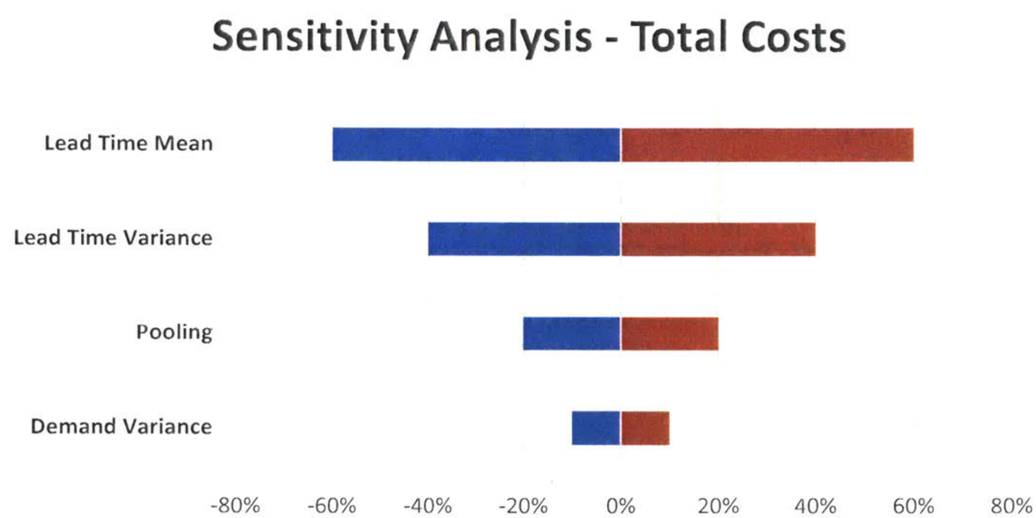


Figure 5-7: Total Cost - Sensitivity analysis

On the other it is reasonable to assume that a strategic and wholesome evaluation of SKUs would uncover significant saving opportunities in regards to sourcing, purchasing, and supply chain costs, with appropriate material quality and risk constraints.

5.4.3. Increase in Demand Variability

The significance of increasing demand variability in the supply chain at utilities is not trivial. Aging networks, growing population, grid innovations and growing occurrences of extreme weather conditions, all induce additional stress on the already stressed system.

In our model we identified that an increase in demand can be mitigated by reducing variations in that demand or by pooling inventory. The two alternatives resulted in similar results – improvement of 24% and 22% for variance control and inventory pooling, respectively. The difference in these results however, is not statistically significant, therefore both are equally good. This outcome is partially intuitive, since the goal of inventory pooling is to consolidate the signal of several demand generating sources, thus flattening the observed demand and reduce variation.

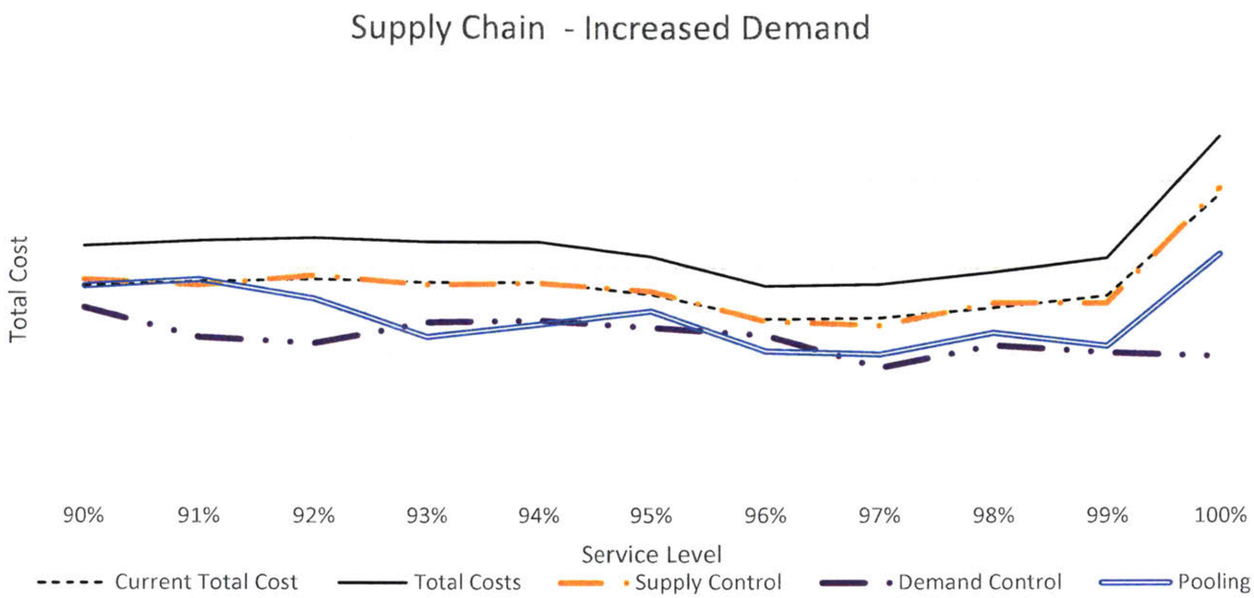


Figure 5-8: Supply Chain - Increased demand

The two methods, controlling for demand variance and inventory pooling, may be undertaken in several ways. Demand variance, for one, may be reduced by increasing visibility into upcoming demand, improving demand forecasting, or aligning material planning with work planning. While these methods may be redundant if any one of them works perfectly, this situation is not likely. Therefore, it would prudent to implement processes improving in each of these aspects.

Similarly, inventory pooling can be implanted in various ways: true pooling, virtual pooling, risk pooling, and so forth. One critical issue to keep in mind is that while some of these methods may reduce one aspect, risk for example, they do not necessarily realize the fool benefits of pooling that can reduce the magnitude of safety stock needed. For example, an inventory network with virtual pooling, giving the different nodes mutual access to inventory, but with a decentralized planning process, may reduce risk by mutually replenishing deficits when needed. However, unless inventory planning is done with the consolidated of both inventory and demand of all nodes, gains in safety stock will not be realized. [5]

5.5. Key Insights

The complexity of supply chains is getting evermore complex. Organizations are not only leveraging global opportunities to drive cost effectiveness and improve market outreach, but they are also increasingly integrating with suppliers and customers to increase end-to-end value. However, the challenge of accounting for internal dependencies and evaluating the effects of decisions is growing appropriately.

In addition, depending on the industry, priorities and cost structure, different variables will influence the objective function, not only at different extents, but also with different gradient profiles. In effect, this means that the effect of some of the variables are not necessarily linear to time, service level, or cost. For example, in our analysis we find that the risk and cost of underage, i.e. not meeting demand, rapidly decreases between 88% and 92% service level, although it maintains its significance even after 92% service level.

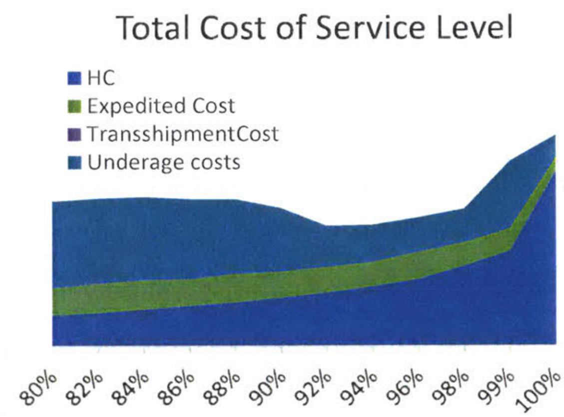


Figure 5-9: Total Cost of Service Level

We demonstrate in the ability to identify behaviors and dependencies that underline the performance of supply chains. Furthermore, we show that implementing a supply chain simulation uncovers second and third tier implications of possible decisions allowing decision makers the tools to adequately assess alternatives.

In this thesis, we present an approach that uses locally available data to evaluate the cross-supply chain effects of a proposed forecast improvement. The results we show illustrate that although it is obvious that system performance can improve with enhanced forecast abilities, the extent of the improvement is dependent on fit of the forecast parameters to the policy of the material. Particularly, the ratio between the time-horizon of the of the forecast and the responsiveness of the supply chain, as well as the weights of performance drivers, for instance, the ratio between expedition costs and holding costs.

Chapter 6. Conclusion

The internal supply chain team has been experiencing high levels of mismatch between the forecast for material demand to the actual material demand. In this thesis, we present a novel approach for demand forecasting using data mining techniques to increase visibility into actual demand. In order to valuate the effects of the possible improvement, we offer an approach to model and scale supply chain networks using locally available data, allowing for a comprehensive evaluation of the performance of the supply chain.

To improve forecasting capabilities we propose the use of data mining techniques, to identify underlying behaviors in the consumption data. In this thesis, we present and discuss the methodology for this approach in addition to an analysis of the data. The structure and characteristics of the demand data are comprehensively discussed, as well as the challenges and sources of these challenges. We further offer several approaches to overcome these challenges, which could be investigated in future studies.

In this thesis we also demonstrate the use of network simulation to evaluate overall supply chain performance, and propose an approach of using locally available data. The benefits of this approach with limited visibility is the ability to create and scale a model of a supply chain external to and with limited visibility from the local supply chain. We use this approach to evaluate the effects of implementing advanced forecasting methodologies.

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