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An Automation System for Optimizing a Supply Chain Network Design under the Influence of Demand Uncertainty

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AN AUTOMATION SYSTEM FOR OPTIMIZING AN INTEGRATED SUPPLY CHAIN NETWORK DESIGN UNDER THE INFLUENCE OF DEMAND UNCERTAINTY

A thesis submitted in partial satisfaction
of the requirements for the degree of

MASTER OF SCIENCE

in

TECHNOLOGY & INFORMATION MANAGEMENT

by

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Notation: Demand Forecasting

γ	smoothing constant for seasonality	19
S_i	seasonal factor for period i, $(i = 1, 2, \ldots, t)$	19
t	current or present time	19
TS	tracking signal	33
$\mathbb{Y}$	$(d_1)^2 + (d_2)^2 + \cdots + (d_i)^2 = \sum_{i=0}^{t}(d_i)^2$	19

Notation: Inventory Management

Notation: Supply Chain Network Design

Notation: Scenario Planning

i	index value for scenarios	68
n	number of total scenarios	68
p_i	scenario probability(%) of occurence for $i = 1, \ldots, n$	68
s_i	scenario s_i for $i = 1, \ldots, n$	68
$\boldsymbol{S}$	probability weighted sum of best future scenario	68

Abstract

An Automation System for Optimizing a Supply Chain Network Design under the Influence of Demand Uncertainty

by

Rany Polany

This research develops and applies an integrated hierarchical framework for modeling a multi-echelon supply chain network design, under the influence of demand uncertainty. The framework is a layered integration of two levels: macro, high-level scenario planning combined with micro, low-level Monte Carlo simulation of uncertainties in demand. To facilitate rapid simulation of the effects of demand uncertainty, the integrated framework was implemented as a dashboard automation system using Microsoft Excel®, Risk Solver, and Visual Basic. The integrated framework has been applied to the problem of quantifying the effects of demand uncertainty on total cost in multi-echelon supply chain network design for high-tech products.

Dedication

To my wife, Raya, and family. Thank you for all your support. I love you.

Acknowledgments

This work was made possible by the exceptional teaching prowess of Subhas Desa who supervised this research and served as the Chair of the thesis committee. In addition, the hierarchical framework that the author develops and applies in this thesis was conceived by Subhas. The author is grateful for the patience and commitment Subhas provided towards supporting this research. It was an honor to be his student.

The author thanks the thesis committee members, Patrick E. Mantey and Nirvikar Singh, for their time and feedback in supporting this work.

1 Introduction

1.1 Motivation

This work investigates how a manufacturing firm can minimize total cost of a supply chain by utilizing a rapid prototyping software simulation system. A competitive manufacturing firm must take into account the entire supply chain (SC) because it is concerned with maximizing profitability, defined by:

$$\begin{pmatrix}\text{supply chain}\\ \text{profitability}\end{pmatrix} \triangleq \begin{pmatrix}\text{revenue from}\\ \text{the end customer}\end{pmatrix} - \begin{pmatrix}\text{total costs incurred in}\\ \text{in the entire supply chain}\end{pmatrix}. \tag{1.1}$$

By taking into account the entire SC, the manufacturing firm is able to view the flow of product, cash, and information between the customers and suppliers to maximize the profitability of the entire chain. Forecasting and error analysis provides the ability to adequately respond to customer needs (thereby generating revenue) and simultaneously to minimize the total costs. The result is the increased SC profitability. A tightly connected inventory management system can reduce costs and increase profits (Desa, 2011) and therefore the firm's inventory needs to be tightly connected to the distribution network. The facility locations need to be placed within an area that promotes the emphasis of the "market-dominance strategy and regional merchandising" (Chopra and Meindl, 2010). Optimized transportation considerations are needed to reduce the costs of making deliveries between the facilities. As part of the approach to maximize profit, the overall business objective is to reduce the costs of the entire SC. Therefore our focus is on the minimization of total costs.

As defined by Chopra and Meindl (2010), the total information system contributes significantly to the increase in profitability because it links the headquarters, suppliers, manufacturers and the entire distribution channel. A tightly integrated information system that is connected to the entire supply chain can provide more accurate forecasting to better match the customer needs and provide a competitive advantage in the marketplace. The ideal supply chain management-of-information system for the future is realizable, but only with the right processes and information technology systems. In order to achieve success, firms must:

1. Enable closed loop collaborative planning processes across the value chain;
2. Have complete supply chain visibility;
3. Implement an effective automation system; and
4. React immediately to disruptions in supply chains.

For the ideal supply chain management system to be realized, a firm must build a responsive supply chain of information, not inventory (Desa, 2011). Due to variations of the demand, at any given time, the firms needs additional inventory in-stock, referred to as safety stock, not to run out of inventory. The safety stock serves as a buffer for the variable fluctuations in demand. Figure 1 is an idealized plot of the ordering cycle, over time (Desa, 2011). The economic order quantity (EOQ), Q_L, is the calculated fixed order quantity that is submitted to the supplier to replenish inventory, where L is the lead-time from the supplier. The ROP is the reorder-point. The D_L is the demand during lead-time. The D_w is the weekly demand. The T is the total time, which is one year. The n is the number of shipments. The ss is the safety stock quantity. The sum of the Q_L and safety inventory, ss, represents the maximum quantity of inventory on-hand.

The cycle inventory is defined as the average in-stock inventory that is being used to meet the demand over a replenishment cycle and formulated by:

$$\text{Cycle Inventory} \triangleq \frac{1}{T}\int_0^T Q_L\,dt = \frac{1}{T}\left(\frac{1}{2}TQ_L\right) = \frac{Q_L}{2}, \tag{1.2}$$

where T is the cycle replenishment time and Q_L is the number of units per shipment from the supplier (also referred to as the lot size). The horizontal dotted line represents the amount of cycle inventory in-stock at any given at any given time, over an

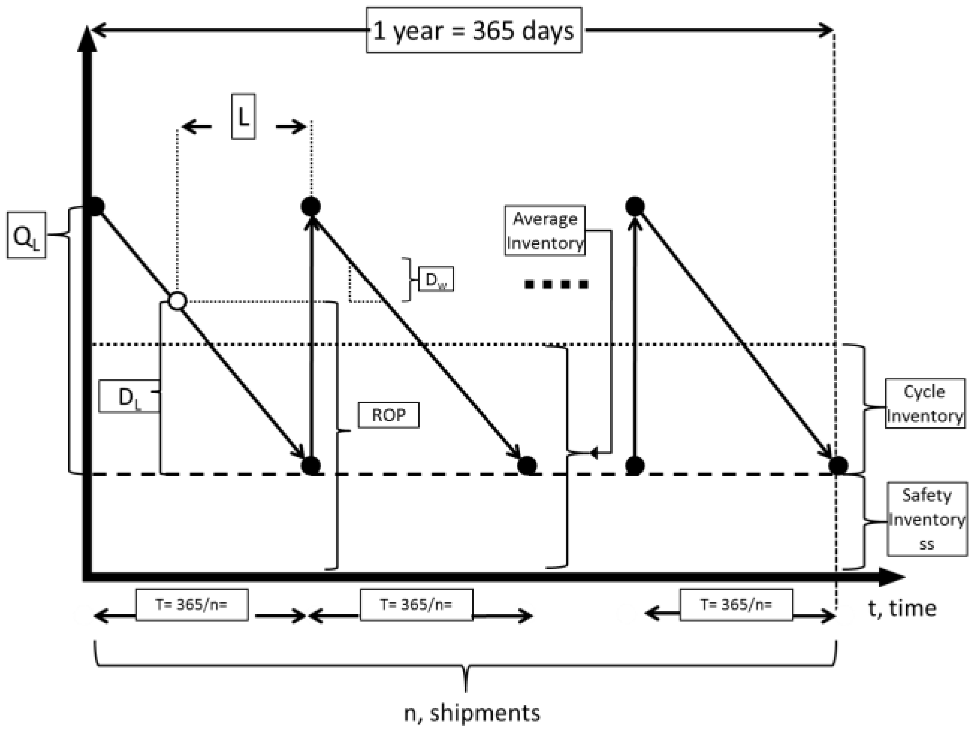


Figure 1: Idealized plot of annual inventory ordering cycle.

annualized basis of n shipments. Due to the variations of the demand occurring during the transport of the replenishment inventory, the quantity of on-hand (safety stock, ss) at the time of receipt of the replenishment delivery varies, sometimes significantly. The horizontal dashed line in Figure 1, representing the safety stock quantity, reflects the amount of inventory that should be in stock, at any given time, over an annualized basis of n shipments. An important point to observe in Figure 1 is that the safety inventory remains relatively constant over an annualized basis. Therefore, evaluating the safety stock is not a valid approach to study the uncertainty in a supply chain because over a long-term basis is does not fluctuate.

The safety inventory quantity is calculated using the mean absolute deviation MAD of the forecast error of the historical demand data, the cycle service level CSL and the lead-time, L. The MAD is formulated as:

$$MAD_n \triangleq \frac{1}{n}\sum_{t=1}^{n} |F_i - D_i| \,, \tag{1.3}$$

where F_i is the forecast of demand for the period, $i = 1, 2, \ldots, t(t = presenttime)$, and D_i is the actual observed demand for the period i. The CSL is "a fraction of the replenishment cycles that end with all the customer demand being met" (Chopra and Meindl, 2010). The safety stock quantity is formulated as:

$$\text{Safety Stock (qty)}, \, ss \triangleq F_z^{-1}(CSL)\sqrt{L}\sigma_D = F_z^{-1}(CSL)\sigma_L. \tag{1.4}$$

Following Chopra and Meindl (2010); Desa (2011), the inverse of the normalized normal distribution function is denoted $F_z^{-1}(p)$, with the subscript z indicating the normalization to a mean, $\mu = 0$, and standard deviation, $\sigma = 1$, thus $F_z^{-1}(p) = F^{-1}(p, \mu = 0, \sigma = 1)$. The standard deviation of the demand, σ_D, is defined as $\sigma_D \approx 1.25 * MAD$. The standard deviation of demand, during the lead-time, σ_L, is defined as $\sigma_L = \sqrt{L}\sigma_D$. The average inventory, at any given time over an annual basis of n shipments for a desired CSL and given lead-time, is the sum of the cycle and the safety inventory:

$$\begin{aligned} \text{Average Inventory} &= \text{Cycle Inventory} + \text{Safety Inventory} && (1.5) \\ &= F_z^{-1}(CSL)\sqrt{L}\sigma_D && (1.6) \\ &= F_z^{-1}(CSL)\sigma_L. && (1.7) \end{aligned}$$

Following the procedure to simulate variance of demand on annual inventory supply by (Ragsdale, 2011) and Boute and Lambrecht (2009), shown in Figure 2 is Trial#1 sample of ten thousand (#1 of 10,000) of a Monte-Carlo simulation that illustrates the effect of increasing the coefficient of variation (CV) of the demand on the annual cycles of supply.

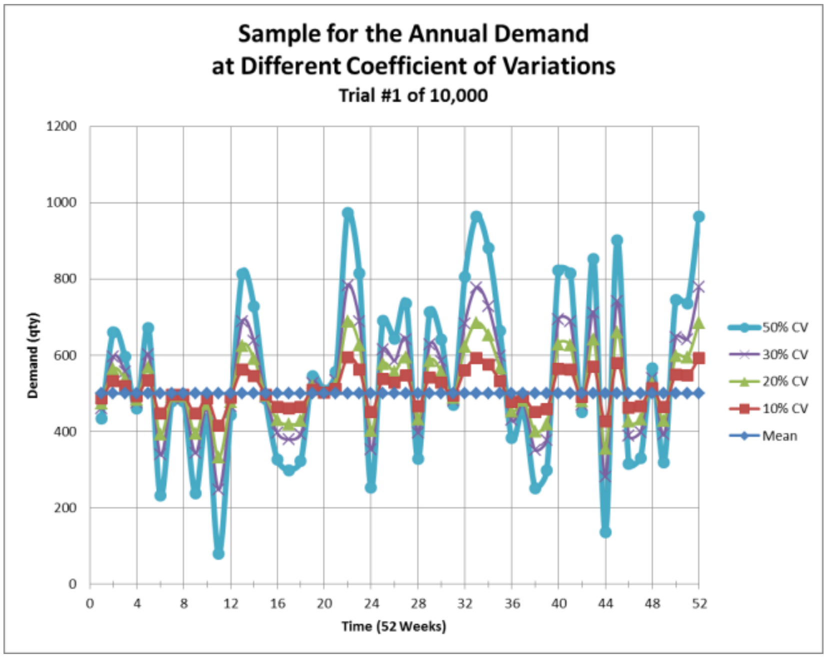


Figure 2: Sample for the annual demand at different parameters of the *coefficient of variations of demand* (Trial 1 of 10,000).

Observe that as the demand increases, the amplitude of the cycle of the demand quantity increases. Therefore, we can learn from this figure that as the coefficient of variation of demand is increased, the coefficient of variation of the supply must also increase in order to meet the demand and main good coordination in the supply chain network.

Our work investigates the above stated relationship between coefficient of variation of demand and the coefficient of variation of supply, under the influence of demand uncertainty, for a multi-echelon supply chain network on a long-term (e.g., annualized) basis.

1.2 Problem Description

This research work studies and quantifies the influence of demand uncertainty on the multi-echelon supply chain network, shown in Figure 3, and, the impact to the decisions to open or close facilities, based on an objective function to minimize total cost. The problem which is investigated is to measure and quantify the effect of the changing the coefficient of variation of demand, $(CV)_D$, on the corresponding coefficient of supply, $(CV)_S$ and the total cost, TC, of the supply chain network.

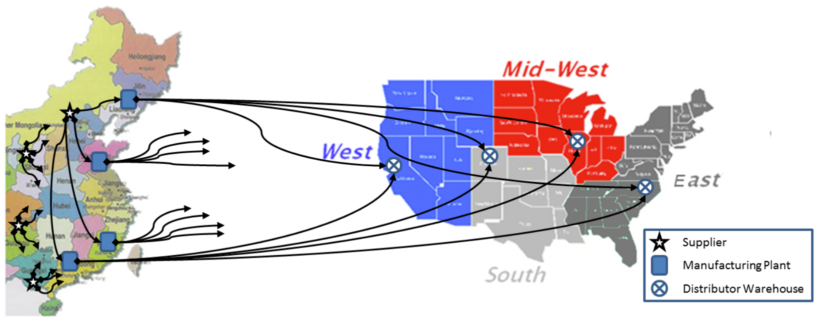


Figure 3: International supply chain network for information technology components.

As shown in Figure 3, the firm has four different suppliers and manufacturing plants in China and imports the finished product to the USA. The products are transported across the Pacific Ocean, via air and ocean freight, to distributor warehouses in the United States that are located throughout four different regions (West, South, Mid-West, East). From the distributor warehouses, the products are consolidated and delivered to various retailers in a region, via ground freight (e.g., UPS), to meet the end-user demand.

1.3 Problem Statement

This work addresses two problems:

(1) The first problem is to investigate a risk-based approach to uncertainty modeling of a supply chain network for high-tech firms that manufacturer and distribute products to retailers. This work presents a process, and an integrated hierarchical framework, that can be efficiently implemented into a automation system to help business managers solve complex supply chain problems. As more and more competitive firms are looking for a means to reduce cost, off-shore manufacturing is

helping to meet this objective, due to the lower cost of oversea resources. Therefore, our work explores how a high-tech firm, in the business of selling computer components, can optimize their supply chain network network when faced with demand uncertainty.

(2) The second problem is to research and address the problem of supply chain management optimization problems with a rapid software-prototyping approach for developing an automation system for the purpose of developing responsive, and efficient, information based supply chain, at a low development cost. This work presents a process for implementing an integrated hierarchical framework into an information based automation system that is able to automate the quantitative analysis of an integrated supply chain system. The automation system is developed using rapid software development tools: (1) Microsoft® Excel; (2) Rick Solver Platform; and (3) VBA programming language. The integrated framework consists of a hierarchical approach to handling uncertainty at the macro and micro level.

Our work creates a process for developing a rapid prototype, of a low cost automation system, that can be used to efficiently optimize and simulate the entire supply chain, under the influence of demand uncertainty. The context of this work is applied to a facility location problem within a multi-stage supply chain. Our work builds up from a two-stage deterministic supply chain network to a multi-stage problem with integration of scenario planning and probabilistic parametric uncertainty modeling. The decisions that are addressed, using a total cost minimization objective function, are:

(a) The facilities to be opened or closed; and

(b) The quantity of product flow between open facilities

1.4 Summary of Research Contributions

The prioritized contributions provided in this research are:

(1) A process for designing a supply chain network, under the influence of demand uncertainty, that addresses uncertainty at two levels(Figures 20, 22 and 23; Sections 3.3, 3.4 and 4.5:

Level 1: Macro (scenario planning)(Section 4.2)

Level 2: Micro (Monte Carlo simulation)(Sections 3.4, 4.5.4 and 4.5.5)

The two-levels for modeling uncertainty are integrated together in a structured process to develop an *integrated hierarchical framework*. Specifically, the relationship of the *coefficient of variation in demand (input)* versus two outputs, *(1) coefficient of variation in supply* and *(2) total costs (output)*, are studied using the *integrated framework*.

The importance of this contribution is that it provides a business manager with an integrated framework to quickly simulate a supply chain network design with an *integrated framework* under the influence of demand uncertainty. This research can help improve the decision-making in the organization in situations where a broad set of scenarios need to be considered (macro), each with a probability of occurrence. Then utilizing the optimal future scenario, a parametric probability approach is used to model the all the possible outcome (micro).

(2) An automated dashboard based system for implementing the integrated framework using $n = 3$ scenarios (macro) and Monte Carlo simulation (micro). (Figures 37 and 39 to 41; Sections 4 and 4.5)

The importance of this contribution is that it demonstrates design and programming in Excel with Visual Basic the automation of the *integrated framework* developed in this work. And, shows the application of studying the effect of demand uncertainty (input) in a multi-echelon supply chain network design and on both the supply quantity and total cost (output).

(3) Implementation and simulation of the *integrated framework* of a four suppliers, four manufacturers, four distributors, and four retailers supply chain network design, under the influence of uncertainty, for a high tech firm to illustrate the application of the automation framework (Figures 46 to 50; Section 5). to demonstrate the application of the *Step 3: Facilities Management* software-automation module using the *integrated framework* and the software automation. The case study illustration has a two-step approach to the simulation and numerical analysis to modeling demand uncertainty in a supply chain network design.

Step 1: **Calibration**: A step-wise process to work through two calibration problems, each with known inputs and known expected outputs. The purpose of executing the calibration problems is to validate that the implementation process (e.g., formulations, code programming, etc.) of the framework have been constructed correctly.

Step 2: **Simulation**: A process to perform a simulation and numerical analysis using a normal distribution function to represent the demand as the input data with unknown supply quantity and total cost outputs. This process was performed using a Base Case, Case 1, 2, and 3 each with $n = 3$ scenarios for product cost, fixed facilities costs, and facility capacity. The results of each analysis are plotted in order to interpret and draw conclusions about the supply chain network design. The analysis of the case studies measures the effect of increasing the *coefficient of variation of demand* on the *coefficient of variation of supply* and measures the effect on total cost. Section 5 describes the implementation of the case study and numerical analysis.

The importance of this contribution is that it illustrates the application of the rapid simulation framework of the integrated framework to draw conclusions which can quickly help the decision making procedures of a business manager. This work shows that the integrated framework can quickly yield an improvement of up to 23% as compared to other heuristic and probabilistic approachs, in a rapid low-cost software-automation environment.

(4) A process and software modules programmed to forecast annual average demand (Figures 4 to 16; Sections 3.1, 4.3 and 7) and related inventory quantities (Figure 17; Sections 3.2, 4.4 and 7).

With the integrated framework and software automation dashboard developed in this work, the supply chain network designer/analyst can performing the following:

(1) Set-up and simulate a nominal supply chain network scenario and determine total cost, which facilities are open and closed, the product flows between facilities, and total supply required to meet demand.The software automation system can support up to four of each: Supplier, manufacturer, distributor, retail, demand region.

(2) Define and simulate the most feasible scenarios based on a structured process of identifying the key uncertainties and consolidating into appropriate high and low configurations. For each scenario, the design/analyst can quantitatively study the effect of demand uncertainty on the outcome of variation in supply and the total cost of the supply chain network.

(3) Utilizing an integrated framework of scenarios (macro) and Monte Carlo simulation (micro) the designer/analyst can simulate for range of possibilities around the best optimal scenario.

(4) Utilizing the integrated Monte Carlo simulation method with 10,000 trials per simulation to adjust the range of the demand uncertainty, using a normal distribution, from 0σ to $\pm 6\sigma$.

(5) Utilizing the dashboard and GUI of the integrated automation system to quickly generate a visualization map of the optimal configuration of the supply chain network.

Therefore, given uncertainty in demand within a multi-echelon supply chain network, the simulation performed in this work using the integrated framework within an automated software tool (using Excel and Visual Basic) can be used to provide quantitative answers for the following questions:

(1) Which facilities should be opened or closed?

(2) What is the optimal product flow quantity between open facilities?

(3) What is the maximum threshold in variation of *supply* that can be tolerated for maintaining good coordination in supply chain network?

(4) What is the maximum threshold in variation of *demand* that can be tolerated for maintaining good coordination in supply chain network?

(5) What is the expected total cost of the supply chain network?

1.5 Organization of the Work

Section 1 introduces the motivation for the work, the problem statement that is being researched, the summary of the related works and the research contributions that result for this work. In Section 2 is discussed the related works and their influence on this work. Section 4 discusses an step-wise approach to the implementation process of the integrated framework presented in this work, along with the construction of the automation framework, which is utilized in the case study simulations. Section 5 is a simulation study and numerical analysis of a set of two calibration problems and a case study. Section 6 is the summary of the results. Lastly, Section 7 gives the conclusion and future work.

2 Related Work

The related literature for our work is defined in the following domains:

(1) Demand forecasting and inventory management

(2) Supply chain network modeling

(3) Uncertainty modeling using a two-level hierarchical framework

Level 1: Scenario planning (macro)

Level 2: Monte Carlo simulation (micro)

2.1 Demand Forecasting and Inventory Management

The text by Chopra and Meindl (2010, chap. 7-12) and lecture content by (Desa, 2011) provided the strategy, planning and operational background information on demand forecasting and inventory management. From these works we adopt and apply the theory towards the implementation approaches discussed in Section 3.

2.2 Supply Chain Network Modeling

2.2.1 Overview of the Supply Chain Network

Our work reviewed various forms of supply networks discussed by Desa (2011); Tsiakis et al. (2001); Chopra and Meindl (2010); Ferreira (2009); Ding et al. (2007); Peidro et al. (2009); Persson and Olhager (2002,?); Snyder (2006); You and Grossmann (2010) to develop and review the facilities location networking model. The related works on supply chain networks is divided into two categories and the theory and approach we use is discussed in detail in Section 3.3:

1. Two-stage networks

2. Multi-echelon networks

2.2.2 Two-stage Supply Chain Network

In the early work by Sridharan (1995), the authors introduced the formulations for the capacitate plant problem, which influenced the work towards understand the formulations of the two-stage network. The work by Swaminathan et al. (1998) provided background information on an architecture structure for handling supply chain modeling and the authors developed the terminology for utilizing a "multiagents" approach to handling the priority of inputs and outputs, during supply chain computations. The recent text by Chopra and Meindl (2010) are adopted and developed many of the Microsoft® Excel worksheet structures used in the software platform that was developed as part of this research. The authors (Chopra and Meindl, 2010) have developed clear and comprehensive examples for building the necessary worksheets utilizing Microsoft® Excel. Additionally, the reference is comprehensive to many areas of supply chain management.

2.2.3 Multi-Echelon Supply Chain Network

In the work by Tsiakis et al. (2001) the authors provide four significant contributions that significantly influenced our work:

(1) A detailed literature review of supply chain models, sorted by model type, model features, operational decisions, strategic functions, and cost functions. The authors developed a summary table reviewing related works up to that point in time. The table is useful to our work because it summarizes the historical references.

(2) A formulation for a heuristic multi-echelon, multi-product supply chain network optimization. The authors presented a multi-echelon network diagram, and the formulations for optimizing a steady-state multi-echelon supply chain network in the work. In their work, the authors considered different product families and the transportation of materials between plants. In our work, the costs are consolidated into the product flow costs.

(3) A scenario-based approach to handle uncertainty in a supply chain model. The authors provided a discussion about the reasoning for using a scenario-based approach. The reasoning is due to the practicality of the approach for reducing the computing resources and increasing speed of attaining a reasonable solution. By condensing many uncertainties into a small number of discrete realizations, which broadly captures the entire spectrum of stochastic quantities, reduces the requirement for the computing resources to quantitatively attain a robust solution to the problem.

(4) The work is expanded with a framework to optimize the network configuration across several scenarios. To handle this method, the authors introduced the Ψ_s to represent the probability of a scenario, s, occurring with the sum of all $\sum_{s=1}^{NS} \Psi_s = 1$ with $NS=$ total number of scenarios.

(5) Lastly, the authors further expanded the work by introducing the superscript $[s]$ on the notation of the operating variables of the production and transportation flows, to represent the different values for each scenario. The constraints were also updated for each scenario. The binary and capacity variables remain unchanged because the optimization is for one single network.

(6) A case study to illustrate the implement of the formulations and theory was also included.

The implementation of the multi-echelon network developed by these authors is instrumental to our work. The contributions discussed above are leveraged into the strategy and framework of our work.

In the work by Ferreira (2009), a similar approach to our work was developed, including the utilization of the Risk Solver Platform in Microsoft® Excel. However, the author clearly states (page 3 of his work) the specific intent is to avoid working with demand uncertainty, and rather to work with deterministic demand. Our work specifically investigates and quantifies the issues when considering demand uncertainty, and more specifically, when doing so with probabilistic approaches and it differs in that respect from Ferreira (2009).

In Section 3, we re-examine the formulations (Tsiakis et al., 2001; Georgiadis et al., 2011; Chopra and Meindl, 2010), and then implement the formulations (Section 4) into a dashboard-based automation system which is used to study the influence of demand uncertainty on the supply chain network design.

2.3 The Influence of Uncertainty at the Macro and Micro Levels

2.3.1 Macro Level: Scenario Planning

The construction of the scenarios in our work follows the process for scenario planning as presented in the works by Vanston et al. (1977); Schoemaker (1991, 1995) and with discussion with Chao (2012) of Seagate, Inc. These sources provided the background on how to consolidate many future uncertainties into a few possible scenarios. The consolidation process follows a structured step-wise approach that is discussed Section 3.4.3.

2.3.2 Micro Level: Monte Carlo Simulation

Based on the text developed by Hillier and Lieberman (2005), we learn that a suitable approach to a modeling uncertainty is the Monte Carlo technique. The use of Monte Carlo simulation, for supply chain network analysis, is substantiated by the work of Schmitt and Singh (2009), in which the authors modeled inventory flow and disruption using Monte Carlo simulation. Our work is further influenced by various simulations (Junga et al., 2004; Ragsdale, 2011; Boute and Lambrecht, 2009; Mun, 2006; Persson and Olhager, 2002; Peidro et al., 2009; UCLA ATS Statistical Consulting Group, 2011; Snyder, 2006) that study the influence of uncertainty on supply chain networks.

2.4 Dashboard/Cockpit Automation

The texts by Alexander (2007) and Eckerson (2010) provide dashboard examples used by industry and discuss how these tools can augment the decision making process. The key attribute of the dashboard is to facilitate the centralized presentation of the summary data in graphical format and allow the user to instantly update the input parameters through point-and-click controls (Eckerson, 2010). In our work, we leverage the lessons from these sources to create our own cockpit dashboard designs.

Our work considers and integrates the Excel worksheet architecture and theories developed by Tsiakis et al. (2001); Chopra and Meindl (2010); Ragsdale (2011); Boute and Lambrecht (2009); Ferreira (2009). The Microsoft platform has a well-developed on-line support and reference system through the MSDN (Microsoft Developer Network). The references for Solver Foundation 3.0 (Mirosoft-MSDN, 2011), VBA language shapes (Hiestand, 2008), and Excel Risk Solver Platform functions in a VBA macro (Bovey et al., 2009; Frontline Systems, Inc., 2011) were utilized to understand how to develop the needed automation for computation and drawing of shapes. The text by Hiestand (2008) provided several use-case scenarios and programming guidelines for performing numerical analysis and computations utilizing the VBA programming language. The text by Bovey et al. (2009) and reference guide by Frontline Systems, Inc. (2011) discusses robust developments for programming in Microsoft® VBA and Excel. These works contain detailed examples of high level of technicality. The lessons from these works are adapted into the product design and code programming of our work which is provided in the *Appendix: VBA Code for the Modules in Section 7.*

3 Theory and Framework

In our work, the theory and framework are based on four prioritized components:

(1) Uncertainty modeling, using a two-level hierarchical framework

Level 1: Scenario planning at the macro level

Level 2: Monte Carlo simulation at the micro level

(2) Supply chain network modeling

(3) Demand forecasting and inventory modeling

(4) Dashboard/cockpit automation

The following sections present the discussion of the four components in the following sequence: (1) demand forecasting and inventory modeling which feeds into the (2) supply chain network modeling which then feeds into the (3) uncertainty modeling and all of this is encapsulated within a (4) dashboard automation system.

3.1 Demand Forecast Modeling

The formulations in this section are adapted from Desa (2011) and Chopra and Meindl (2010, chap.5). Equations from these authors are used to build the automation software within the Microsoft® Excel framework that is discussed in Section 4.

Notation for time-series forecasting:

$i \triangleq$ index value for a generic period, $(i = 1, 2, \ldots, t)$

$t \triangleq$ current or present time

$p \triangleq$ periodicity

$\ell \triangleq$ index value for a generic future time periods, $(l = 1, 2, ...)$

$r \triangleq$ number of cycles in the data

$N \triangleq$ number of points for computing a moving average

$L_i \triangleq$ level at present time for period i, $(i = 1, 2, \ldots, t)$

$\mathcal{L} \triangleq$ best fit straight line in the standard form of $y = mx + b$

$d_i \triangleq$ perpendicular distance from the point D_i to line $\mathcal{L}$

$D_i \triangleq$ actual demand at period i, $(i = 1, 2, \ldots, t)$

$\overline{D_i} \triangleq$ regressed demand at period i, $(i = 1, 2, \ldots, t)$

$\overline{D_i}' \triangleq$ deseasonalized demand at period i, $(i = 1, 2, \ldots, t)$

$\mathbb{Y} \triangleq$ sum of the perpendicular distances, d_i, for period i, $(i = 1, 2, \ldots, t)$

$$\mathbb{Y} = (d_1)^2 + (d_2)^2 + \cdots + (d_i)^2 = \sum_{i=0}^{t} (d_i)^2,\ (i = 1, 2, \ldots, t)$$

$S_i \triangleq$ seasonal factor

$\alpha \triangleq$ smoothing constant for level

$\beta \triangleq$ smoothing constant for trend

$\gamma \triangleq$ smoothing constant for seasonality

The process to determine the optimal forecasting method and quantify the optimal demand is:

Step 1: Compute the forecasted demand quantity utilizing static and adaptive methods.

Step 2: Determine the forecast error for each method.

Step 3: Utilize the total forecasted demand from the corresponding method with the lowest MAPE (mean absolute percent error) value.

Step 4: Convert the total demand to an average annual demand, $\overline{\mathfrak{D}}$.

In the following subsections is presented the theory and approaches from the related works, as it pertains to the formulations for demand forecasting.

3.1.1 Components of Observed Demand

With any discussion pertaining to observed demand, $\mathcal{O}$, there are two important components to consider:

(1) The systematic component, $\mathcal{S}$, which are the expected values of the demand attained from:

  (a) Level, L is the intercept

  (b) Trend, T is the slope (growth)

  (c) Seasonality, $\mathcal{S}$ is the predictable fluctuation of the demand.

(2) The random component, $\mathcal{R}$, which are the uncertain values of the demand.

As shown in Figure 4, given a historical time series of demand data,$(D_1, D_2, \ldots, D_t)$, the objective is to determine the optimal future demand for D_i for $i = 1, 2, \ldots, t$ (t =present time). Only the systematic component, $\mathcal{S}$, of the demand can be forecasted. The random component, $\mathcal{R}$, cannot be forecasted.

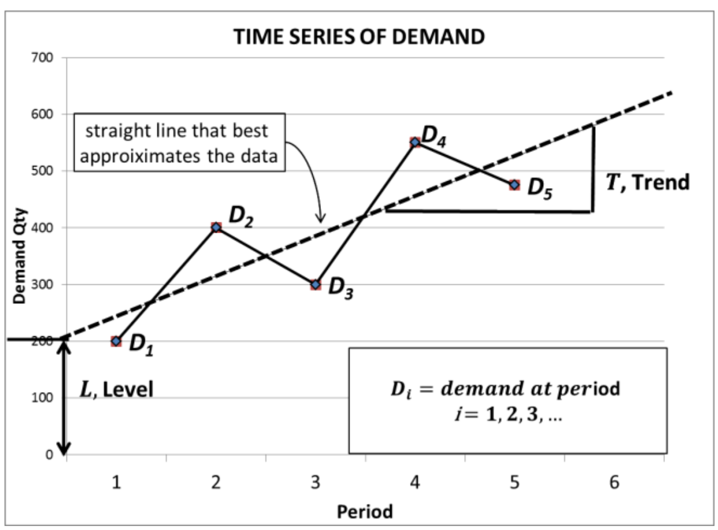


Figure 4: Time series of demand data to determine the level and trend.

There are two types of forecasting methods for analyzing demand:

(1) Static forecasting, in which estimates of the L, T, and $\mathcal{S}$ do not change with time.

(2) Adaptive forecasting, in which estimates of the L, T, and $\mathcal{S}$ update as new real-time data is obtained.

In the following subsections are presented the formulations of the static and adaptive forecasting methods and illustrative examples of how to construct Microsoft® Excel worksheets to compute the forecast.

3.1.2 Static Forecasting Method

Utilizing the least-squares approximation method (aka, linear regression), as shown in Figure 5, finding the straight line that best fits the data is used to estimate the future demand.

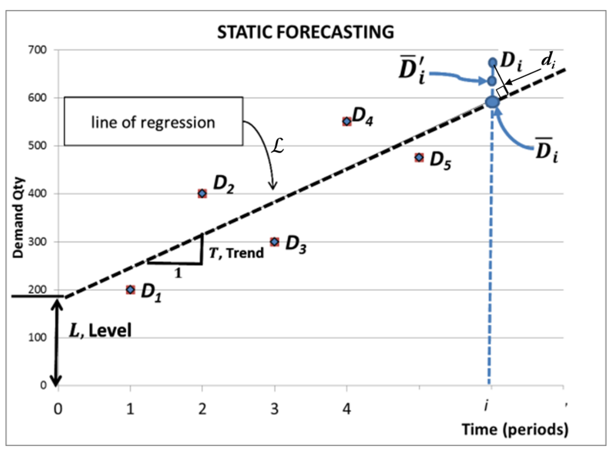


Figure 5: Static forecasting method.

The objective is to determine the equation of the straight line, $\mathcal{L}$, over all the periods, $i = 1, 2, \ldots, t$, in the standard form of $y = mx + b$ that minimizes the sum, $\mathbb{Y}$, of the squared perpendicular distances, d_i, from each demand point, D_i, to the line, $\mathcal{L}$, where m =slope (trend) and b =intercept (level) of the line, $\mathcal{L}$.

The process to compute the time-series static forecast is:

Step 1: Start with demand data, D_i, for $i = 1, 2, \ldots, t$.

Step 2: Compute the deaseasonlized data, $\overline{D}_i^{'}$, for $i = 1, 2, \ldots, t$ by removing the seasonal effect in the demand:

$$\overline{D}_i^{'} = \frac{D_{t-(p/2)} + D_{t+(p/2)} + \displaystyle\sum_{i=t+1-(p/2)}^{t-1+(p/2)} 2(D_i)}{2p}. \tag{3.1}$$

Step 3: Utilizing the $\overline{D}_i^{'}$ results, perform the linear regression data analysis by computing the line, $\mathcal{L}$, to determine $L - \mathit{intercept}$ and the T, trend.

Step 4: With the $L - \mathit{intercept}$ and T values, compute the deseasonlized regressed demand, $\overline{D}_i$, for each period, $i = 1$ to t, for all cycles.

Step 5: Compute the seasonal factor, $\overline{\mathcal{S}}_i$, for each period, $i = 1$ to t, for all cycles:

$$\overline{\mathcal{S}}_i = \frac{D_i}{\overline{D}_i{}^{'}}. \tag{3.2}$$

Step 6: Compute the average seasonal factor, $\overline{\mathcal{S}}$, for each period, p (given r seasonal cycles in the data, for all periods $pt + i, 1 \leq i \leq p$):

$$S_i = \frac{\displaystyle\sum_{j=0}^{r-1} \overline{\mathcal{S}} jp + i}{r}. \tag{3.3}$$

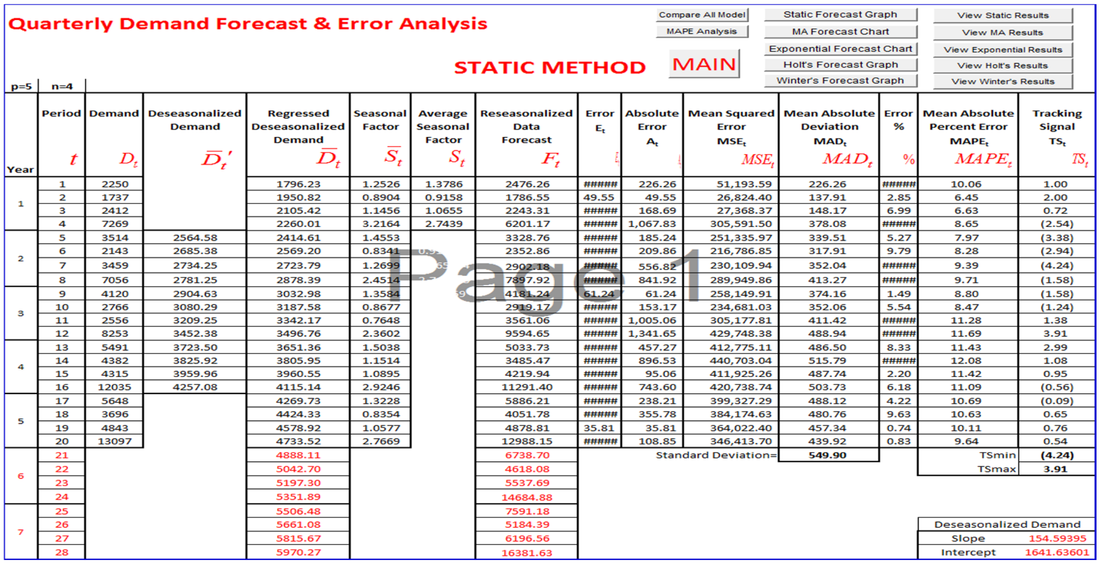
Step 7: Compute the reasonalized data forecast:

$$F_i = \overline{D}_i S_i = (L + iT)S_i. \tag{3.4}$$

Step 8: Compute the forecasted demand for future periods, ℓ, at time $t + \ell$, and $\ell = 1, 2, \ldots$ periods into the future:

$$F_{t+\ell} = \overline{D}_{t+\ell} * S_{t+\ell} = (L + (t + \ell)T) * S_{t+\ell}. \tag{3.5}$$

The *static method* Excel worksheet is formatted as follows:



Quarterly Demand Forecast & Error Analysis

Compare All Model | MAPE Analysis | Static Forecast Graph | MA Forecast Chart | Exponential Forecast Chart | Holt's Forecast Graph | Winter's Forecast Graph | View Static Results | View MA Results | View Exponential Results | View Holt's Results | View Winter's Results

STATIC METHOD

MAIN

p=5 n=4

Year	Period t	Demand D_t	Deseasonalized Demand $\bar{D}_t'$	Regressed Deseasonalized Demand $\bar{D}_t$	Seasonal Factor $\bar{S}_t$	Average Seasonal Factor S_t	Reseasonalized Data Forecast F_t	Error E_t	Absolute Error A_t	Mean Squared Error MSE_t	Mean Absolute Deviation MAD_t	Error %	Mean Absolute Percent Error $MAPE_t$	Tracking Signal TS_t
1	1	2250		1796.23	1.2526	1.3786	2476.26	######	226.26	51,193.59	226.26	######	10.06	1.00
	2	1737		1950.82	0.8904	0.9158	1786.55	49.55	49.55	26,824.40	137.91	2.85	6.45	2.00
	3	2412		2105.42	1.1456	1.0655	2243.31	######	168.69	27,368.37	148.17	6.99	6.63	0.72
	4	7269		2260.01	3.2164	2.7439	6201.17	######	1,067.83	305,591.50	378.08	######	8.65	(2.54)
2	5	3514	2564.58	2414.61	1.4553		3328.76	######	185.24	251,335.97	339.51	5.27	7.97	(3.38)
	6	2143	2685.38	2569.20	0.8341		2352.86	######	209.86	216,786.85	317.91	9.79	8.28	(2.94)
	7	3459	2734.25	2723.79	1.2699		2902.18	######	556.82	230,109.94	352.04	######	9.39	(4.24)
	8	7056	2781.25	2878.39	2.4514		7897.92	######	841.92	289,949.86	413.27	######	9.71	(1.58)
3	9	4120	2904.63	3032.98	1.3584		4181.24	61.24	61.24	258,149.91	374.16	1.49	8.80	(1.58)
	10	2766	3080.29	3187.58	0.8677		2919.17	######	153.17	234,681.03	352.06	5.54	8.47	(1.24)
	11	2556	3209.25	3342.17	0.7648		3561.06	######	1,005.06	305,177.81	411.42	######	11.28	1.38
	12	8253	3452.38	3496.76	2.3602		9594.65	######	1,341.65	429,748.38	488.94	######	11.69	3.91
4	13	5491	3723.50	3651.36	1.5038		5033.73	######	457.27	412,775.11	486.50	8.33	11.43	2.99
	14	4382	3825.92	3805.95	1.1514		3485.47	######	896.53	440,703.04	515.79	######	12.08	1.08
	15	4315	3959.96	3960.55	1.0895		4219.94	######	95.06	411,925.26	487.74	2.20	11.42	0.95
	16	12035	4257.08	4115.14	2.9246		11291.40	######	743.60	420,738.74	503.73	6.18	11.09	(0.56)
5	17	5648		4269.73	1.3228		5886.21	######	238.21	399,327.29	488.12	4.22	10.69	(0.09)
	18	3696		4424.33	0.8354		4051.78	######	355.78	384,174.63	480.76	9.63	10.63	0.65
	19	4843		4578.92	1.0577		4878.81	35.81	35.81	364,022.40	457.34	0.74	10.11	0.76
	20	13097		4733.52	2.7669		12988.15	######	108.85	346,413.70	439.92	0.83	9.64	0.54
6	21			4888.11			6738.70			Standard Deviation=	549.90		TSmin	(4.24)
	22			5042.70			4618.08						TSmax	3.91
	23			5197.30			5537.69							
	24			5351.89			14684.88							
7	25			5506.48			7591.18							
	26			5661.08			5184.39						Deseasonalized Demand	
	27			5815.67			6196.56						Slope	154.59395
	28			5970.27			16381.63						Intercept	1641.63601

Figure 6: Static method worksheet.

The *static method* Excel chart is formatted as follows:

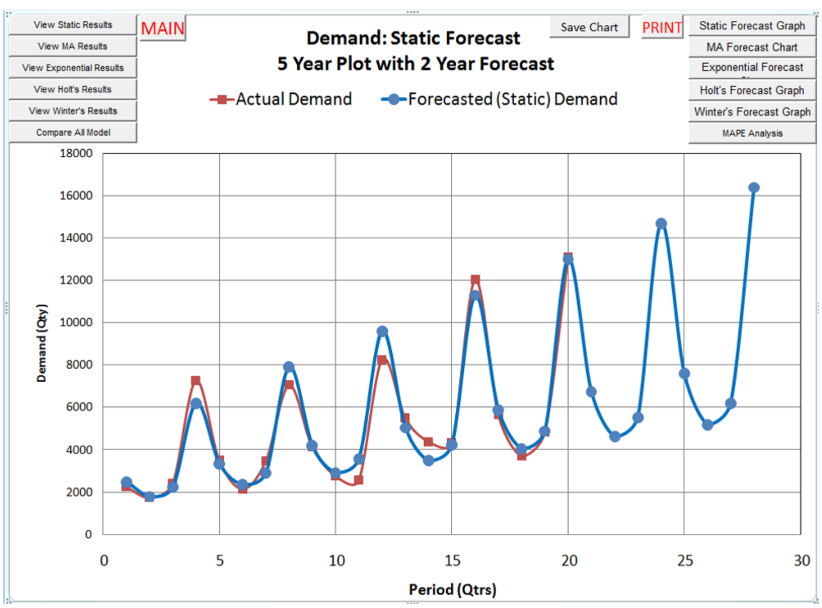


Figure 7: Static method chart.

3.1.3 Moving Average Method

The moving average forecasting treatment uses a series adaptive of formulas (Desa, 2011; Chopra and Meindl, 2010) to compute the demand forecast with the moving average method. This method requires that the systematic component of the demand data, $\mathcal{S}$, has only level.

Step 1: Forecast by choosing N points for computing the moving average ($N - point$ moving average) at time, t:

$$L_t = \frac{D_t + D_t + 1 + \cdots + D_t - N + 1}{N}. \tag{3.6}$$

Step 2: The forecast at the current time, t, is the same as for all future periods, $t + \ell$, $(l = 1, 2, ...)$ and therefore is based on the current estimate of level:

$$F_t = L_t \text{ and } F_{t+l} = L_t. \tag{3.7}$$

Step 3: After observing the demand for period, $t + \ell$, the estimate is revised:

$$L_t = \frac{D_{t+1} + D_t + \cdots + D_t - N - 2}{N} : \tag{3.8}$$

$$F_{t+2} = L_{t+1}$$

$$F_{t+\ell} = L_{t+1}, (t = 0, 1, 2, \dots), (l = 1, 2, ...).$$

By adding the latest observation and dropping the oldest one by proceeding through N periods, the moving average becomes less responsive to the most recently observed demand.

The *moving average* Excel worksheet is formatted as follows:

Monthly Demand Forecast & Error Analysis

Compare All Model | MAPE Analysis | Static Forecast Graph | MA Forecast Chart | Exponential Forecast Chart | Holt's Forecast Graph | Winter's Forecast Graph | View Static Results | View MA Results | View Exponential Results | View Holt's Results | View Winter's Results

MAIN

MOVING AVERAGE (Quaterly)

p=5	n=4										
Year	Period	Demand D_t	Level L_t	Forecast F_t	Error E_t	Absolute Error A_t	Mean Squared Error MSE_t	Mean Absolute Deviation MAD_t	Error %	Mean Absolute Percent Error $MAPE_t$	Tracking Signal TS_t
1	1	2250									
	2	1737									
	3	2412									
	4	7269	3,417.0000								
2	5	3514	3,733.0000	3,417.000	-97.00	97.0	9409.0	97.0	2.8	2.8	-1.00
	6	2143	3,834.5000	3,733.000	1590.00	1590.0	1268754.5	843.5	74.2	38.5	1.77
	7	3459	4,096.2500	3,834.500	375.50	375.5	892836.4	687.5	10.9	29.3	2.72
	8	7056	4,043.0000	4,096.250	-2959.75	2959.8	2859657.3	1255.6	41.9	32.4	-0.87
3	9	4120	4,194.5000	4,043.000	-77.00	77.0	2288911.7	1019.9	1.9	26.3	-1.15
	10	2766	4,350.2500	4,194.500	1428.50	1428.5	2247528.4	1088.0	51.6	30.5	0.24
	11	2556	4,124.5000	4,350.250	1794.25	1794.3	2386357.7	1188.9	70.2	36.2	1.73
	12	8253	4,423.7500	4,124.500	-4128.50	4128.5	4218627.0	1556.3	50.0	37.9	-1.33
4	13	5491	4,766.5000	4,423.750	-1067.25	1067.3	3876448.7	1502.0	19.4	35.9	-2.09
	14	4382	5,170.5000	4,766.500	384.50	384.5	3503587.9	1390.2	8.8	33.2	-1.98
	15	4315	5,610.2500	5,170.500	855.50	855.5	3251614.4	1341.6	19.8	32.0	-1.42
	16	12035	6,555.7500	5,610.250	-6424.75	6424.8	6420431.0	1765.2	53.4	33.7	-4.72
5	17	5648	6,595.0000	6,555.750	907.75	907.8	5989937.0	1699.3	16.1	32.4	-4.37
	18	3696	6,423.5000	6,595.000	2899.00	2899.0	6162384.5	1784.9	78.4	35.7	-2.53
	19	4843	6,555.5000	6,423.500	1580.50	1580.5	5918090.9	1771.3	32.6	35.5	-1.66
	20	13097	6,821.0000	6,555.500	-6541.50	6541.5	8222661.6	2069.5	49.9	36.4	-4.58
6	21			6821.000			Standard Deviation=	2,586.82		TSmin	(4.72)
	22			6821.000						TSmax	2.72
	23			6821.000							
	24			6821.000							
7	25			6821.000							
	26			6821.000							
	27			6821.000							
	28			6821.000							

Page 1

Figure 8: Moving average worksheet.

The *moving average* Excel chart is formatted as follows:

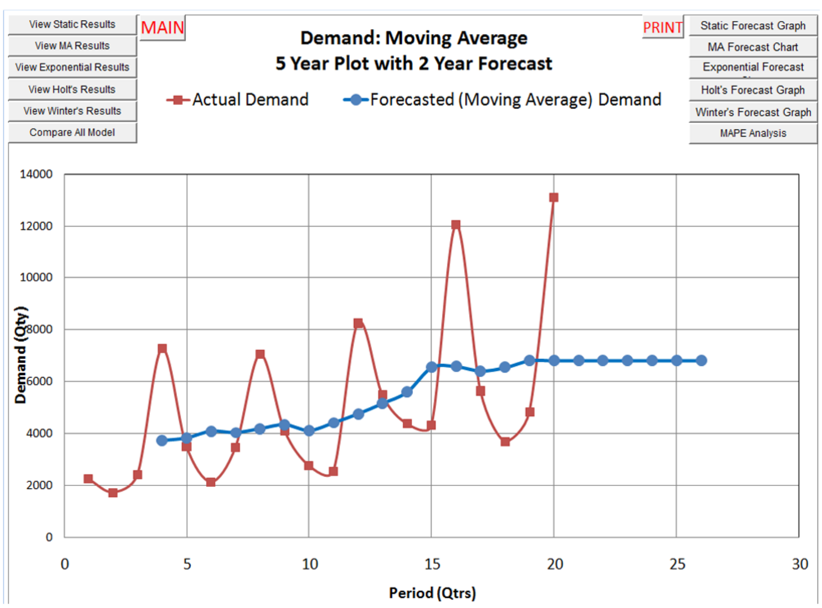


Figure 9: Moving average chart.

3.1.4 Simple Exponential Method

The simple exponential smoothing demand forecasting treatment uses a series of formulas (Desa, 2011; Chopra and Meindl, 2010) to compute the demand forecast with exponential smoothing constants. This method requires that the systematic component of the demand data, $\mathcal{S}$, has only level.

The step-wise process for computing the simple exponential forecasting is:

Step 1: Initialize by finding the average level over the total number of data points, n:

$$L_0 = \frac{1}{n}\sum_{i=1}^{n} D_i. \tag{3.9}$$

Step 2: Forecast for all periods of time, t:

$$F_{t+1} = L_t \tag{3.10}$$

$$F_{t+n} = L_t. \tag{3.11}$$

Step 3: Estimate the error:

$$\begin{aligned} E_1 &\triangleq F_1 - D_1 \\ &= L_0 - D_1. \end{aligned} \tag{3.12}$$

Step 4: Update the level based on the error estimate. If $E_1 > 0$, then F_1 exceeds the actual demand and the coefficients for the level must be adjusted.

Step 5: Adjust the level based on the error:

$$
\begin{aligned}
L_1 &= L_0 - \alpha(E_1) \\
&= L_0 - \alpha(L_0 - D_1) \\
&= \alpha D_1 + (1-\alpha)L_0 \\
&\alpha \ \text{ is the smoothing constant} \\
&0 < \alpha < 1 \qquad\qquad\qquad .
\end{aligned} \tag{3.13}
$$

Step 6: Adjust the level based on the error:

$$
\begin{aligned}
&L_{t+\ell} = \alpha D_{t+\ell} + (1-\alpha)L_t \\
&0 < \alpha < 1 \\
&F_{t+2} = L_{t+1} \\
&\quad\vdots \\
&F_{t+\ell} = L_{t+1} \\
&(t = 1, 2, 3, \ldots), (\ell = 1, 2, 3, \ldots).
\end{aligned} \tag{3.14}
$$

The *exponential smoothing* Excel worksheet is formatted as follows:

Monthly Demand Forecast & Error Analysis

Compare All Model | MAPE Analysis | Static Forecast Graph | MA Forecast Chart | Exponential Forecast Chart | Holt's Forecast Graph | Winter's Forecast Graph | View Static Results | View MA Results | View Exponential Results | View Holt's Results | View Winter's Results

EXPONENTIAL SMOOTHING MAIN

	p=5	n=4									
Year	Period t	Demand D_t	Level L_t	Forecast F_t	Error E_t	Absolute Error A_t	Mean Squared Error MSE_t	Mean Absolute Deviation MAD_t	Error %	Mean Absolute Percent Error $MAPE_t$	Tracking Signal TS_t
	0.00		5,052.10								
1	1	2250	4,771.89	5,052.10	2,802.10	2,802.10	7,851,764.41	2,802.10	124.54	124.54	1.00
	2	1737	4,468.40	4,771.89	3,034.89	3,034.89	8,531,160.86	2,918.50	174.72	149.63	2.00
	3	2412	4,262.76	4,468.40	2,056.40	2,056.40	7,097,035.60	2,631.13	85.26	128.17	3.00
	4	7269	4,563.38	4,262.76	-3,006.24	3,006.24	7,582,145.08	2,724.91	41.36	106.47	1.79
2	5	3514	4,458.45	4,563.38	1,049.38	1,049.38	6,285,957.76	2,389.80	29.86	91.15	2.48
	6	2143	4,226.90	4,458.45	2,315.45	2,315.45	6,131,846.75	2,377.41	108.05	93.96	3.47
	7	3459	4,150.11	4,226.90	767.90	767.90	5,340,107.65	2,147.48	22.20	83.71	4.20
	8	7056	4,440.70	4,150.11	-2,905.89	2,905.89	5,728,117.67	2,242.28	41.18	78.40	2.73
3	9	4120	4,408.63	4,440.70	320.70	320.70	5,103,087.79	2,028.77	7.78	70.55	3.17
	10	2766	4,244.37	4,408.63	1,642.63	1,642.63	4,862,602.45	1,990.16	59.39	69.43	4.06
	11	2556	4,075.53	4,244.37	1,688.37	1,688.37	4,679,691.69	1,962.72	66.06	69.13	4.98
	12	8253	4,493.28	4,075.53	-4,177.47	4,177.47	5,743,988.29	2,147.28	50.62	67.58	2.60
4	13	5491	4,593.05	4,493.28	-997.72	997.72	5,378,716.12	2,058.86	18.17	63.78	2.23
	14	4382	4,571.94	4,593.05	211.05	211.05	4,997,703.69	1,926.87	4.82	59.57	2.49
	15	4315	4,546.25	4,571.94	256.94	256.94	4,668,924.82	1,815.54	5.95	56.00	2.79
	16	12035	5,295.13	4,546.25	-7,488.75	7,488.75	7,882,202.76	2,170.12	62.22	56.39	-1.12
5	17	5648	5,330.41	5,295.13	-352.87	352.87	7,425,868.51	2,063.22	6.25	53.44	-1.35
	18	3696	5,166.97	5,330.41	1,634.41	1,634.41	7,161,726.10	2,039.40	44.22	52.92	-0.56
	19	4843	5,134.57	5,166.97	323.97	323.97	6,790,317.23	1,949.11	6.69	50.49	-0.42
	20	13097	5,930.82	5,134.57	-7,962.43	7,962.43	9,620,812.49	2,249.78	60.80	51.01	-3.91
6	21			5,930.82			Standard Deviation=	2,812.22		TSmin	(3.91)
	22			5,930.82						TSmax	4.98
	23			5,930.82							
	24			5,930.82						alpha=	0.10
7	25			5,930.82							
	26			5,930.82							
	27			5,930.82							
	28			5,930.82							

Figure 10: Exponential smoothing worksheet.

The *exponential smoothing* Excel chart is formatted as follows:

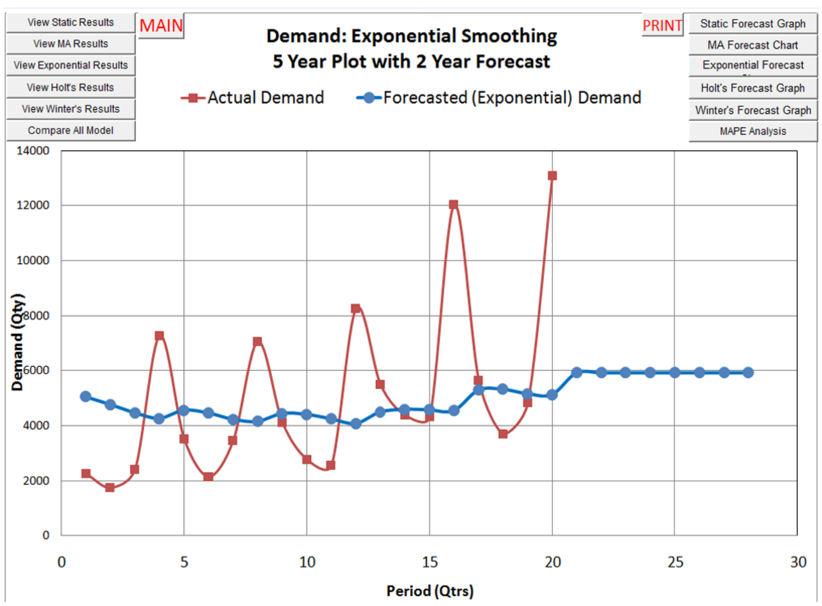


Figure 11: Exponential smoothing chart.

3.1.5 Holt's Method

The Holt's method forecasting treatment uses a series of formulas (Desa, 2011; Chopra and Meindl, 2010) to compute the demand forecast with the Holt's method. The systematic component of the demand data, $\mathcal{S}$, has level and trend (i.e., no seasonality).

Step 1: The Holt's method requires the initial level and trend using a linear regression between demand and time period, t. Obtain the level and trend by running a linear regression of demand, D_t and time, t (b=initial level,L_0 at $t = 0$ and a is initial estimate of trend at T_0):

$$D_t = at + b. \tag{3.15}$$

Step 2: Revise the estimate of the level:

$$T_{t+1} = \beta(L_{t+1} - L_t) + (1 - \beta)T_t \tag{3.16}$$

$$0 < \beta < 0$$

$$F_{t+2} = L_{t+1}$$

β is the smoothing constant for the level.

Step 3: The current forecast for all future periods is based on the current estimate of level:

$$F_{t+1} = L_t + T_t \tag{3.17}$$

and

$$F_{t+1} = L_t + T_t. \tag{3.18}$$

The *Holt's method* Excel worksheet is formatted as follows:

Monthly Demand Forecast & Error Analysis

HOLT'S METHOD

Compare All Model | MAPE Analysis | MAIN | Static Forecast Graph | MA Forecast Chart | Exponential Forecast Chart | Holt's Forecast Graph | Winter's Forecast Graph | View Static Results | View MA Results | View Exponential Results | View Holt's Results | View Winter's Results

Year	Period t	Demand D_t	Level L_t	Trend T_t	Forecast F_t	Error E_t	Absolute Error A_t	Mean Squared Error MSE_t	Mean Absolute Deviation MAD_t	Error %	Mean Absolute Percent Error $MAPE_t$	Tracking Signal TS_t
	p=5	n=4										
	0		2,042.74	286.61								
1	1	2250	2,321.41	285.81	2,329.34	79.34	79.34	6,295.29	79.34	3.53	3.53	1.00
	2	1737	2,520.20	277.11	2,607.22	870.22	870.22	381,790.08	474.78	50.10	26.81	2.00
	3	2412	2,758.78	273.26	2,797.31	385.31	385.31	304,014.50	444.96	15.97	23.20	3.00
	4	7269	3,455.73	315.63	3,032.04	-4,236.96	4,236.96	4,715,977.38	1,392.96	58.29	31.97	-2.08
2	5	3514	3,745.62	313.05	3,771.36	257.36	257.36	3,786,028.64	1,165.84	7.32	27.04	-2.27
	6	2143	3,867.11	293.90	4,058.68	1,915.68	1,915.68	3,766,659.96	1,290.81	89.39	37.43	-0.56
	7	3459	4,090.80	286.88	4,161.01	702.01	702.01	3,298,967.34	1,206.70	20.30	34.99	-0.02
	8	7056	4,645.51	313.66	4,377.68	-2,678.32	2,678.32	3,783,270.23	1,390.65	37.96	35.36	-1.95
3	9	4120	4,875.26	305.27	4,959.17	839.17	839.17	3,441,152.57	1,329.37	20.37	33.69	-1.40
	10	2766	4,939.07	281.12	5,180.52	2,414.52	2,414.52	3,680,029.75	1,437.89	87.29	39.05	0.38
	11	2556	4,953.77	254.48	5,220.19	2,664.19	2,664.19	3,990,747.93	1,549.37	104.23	44.98	2.07
	12	8253	5,512.73	284.93	5,208.26	-3,044.74	3,044.74	4,430,724.74	1,673.99	36.89	44.30	0.10
4	13	5491	5,766.99	281.86	5,797.66	306.66	306.66	4,097,133.55	1,568.81	5.58	41.33	0.30
	14	4382	5,882.17	265.19	6,048.85	1,666.85	1,666.85	4,002,938.44	1,575.81	38.04	41.09	1.36
	15	4315	5,964.13	246.87	6,147.36	1,832.36	1,832.36	3,959,912.50	1,592.91	42.46	41.18	2.49
	16	12035	6,793.40	305.11	6,211.00	-5,824.00	5,824.00	5,832,357.61	1,857.36	48.39	41.63	-1.00
5	17	5648	6,953.45	290.60	7,098.51	1,450.51	1,450.51	5,613,040.39	1,833.42	25.68	40.69	-0.22
	18	3696	6,889.25	255.12	7,244.06	3,548.06	3,548.06	6,000,578.31	1,928.68	96.00	43.77	1.63
	19	4843	6,914.24	232.11	7,144.38	2,301.38	2,301.38	5,963,512.95	1,948.30	47.52	43.96	2.80
	20	13097	7,741.41	291.62	7,146.35	-5,950.65	5,950.65	7,435,849.37	2,148.42	45.44	44.04	-0.23
6	21				9,199.50			Standard Deviation=	2,685.52		TSmin	(2.27)
	22				9,491.11						TSmax	3.00
	23				9,782.73							
	24				10,074.35						alpha=	0.10
7	25				10,365.96						beta=	0.10
	26				10,657.58							
	27				10,949.20						Slope	286.60602
	28				11,240.81						Intercept	2042.73684

Figure 12: Holt's method worksheet.

The *Holt's method* Excel chart is formatted as follows:

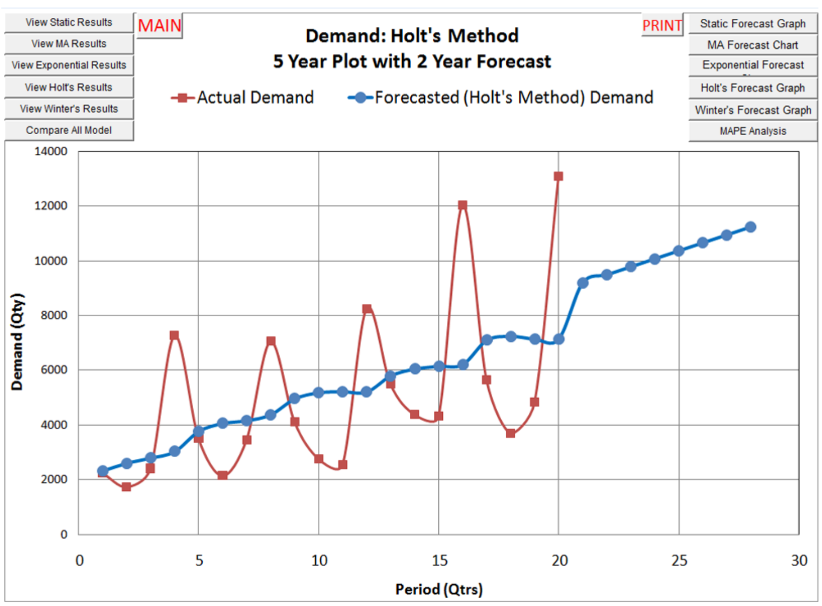


Figure 13: Holt's method chart.

3.1.6 Winter's Method

The Winter's forecasting treatment uses a series of formulas (Desa, 2011; Chopra and Meindl, 2010) to compute the demand forecast with the Winters's method. The systematic component of the demand data, $\mathcal{S}$, has level and trend, with a seasonal factor. The procedure requires the estimate for the initial level and trend from the same method as in the static forecast, and an additional step to revise the estimate of the level. The step-wise process is as follows:

Step 1: Compute L_{t+1}:

$$L_{t+1} = \alpha \left(\frac{D_{t+1}}{S_{t+1}} \right) + (1-\alpha)(L_t + T_t) \tag{3.19}$$

$$0 < \alpha < 1$$

α is a smoothing constant for the level.

Step 2: Compute T_{t+1}:

$$T_{t+1} = \beta \left(L_{t+1} - L_t \right) + (1-\beta) T_t \tag{3.20}$$

$$0 < \beta < 1$$

β is a smoothing constant for the trend.

Step 3: Compute S_{t+p+1}:

$$S_{t+p+1} = \gamma \left(\frac{D_{t+1}}{L_{t+1}} \right) + (1-\gamma)(S_{t+1}) \tag{3.21}$$

$$0 < \gamma < 1$$

γ is a smoothing constant for the seasonal factor.

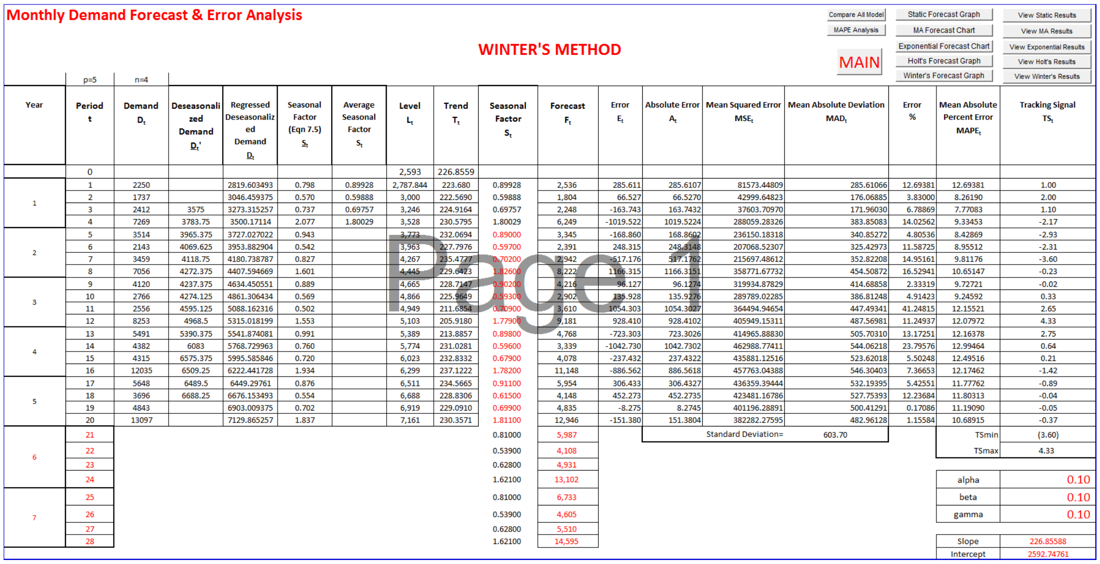
Step 4: Compute the forecast for future periods:

$$F_{t+1} = (L_t + T_t) S_{t+1} \tag{3.22}$$

and

$$F_{t+\ell} = (L_t + \ell T_t) S_{t+1}, (\ell = 1, 2, 3, \dots). \tag{3.23}$$

The *Winter's method* Excel worksheet is formatted as follows:



Year	Period t	Demand D_t	Deseasonalized Demand D_t'	Regressed Deseasonalized Demand D_t	Seasonal Factor (Eqn 7.5) S_t	Average Seasonal Factor S_t	Level L_t	Trend T_t	Seasonal Factor S_t	Forecast F_t	Error E_t	Absolute Error A_t	Mean Squared Error MSE_t	Mean Absolute Deviation MAD_t	Error %	Mean Absolute Percent Error $MAPE_t$	Tracking Signal TS_t
	0						2,593	226.8559									
1	1	2250		2819.603493	0.798	0.89928	2,787.844	223.680	0.89928	2,536	285.611	285.6107	81573.44809	285.61066	12.69381	12.69381	1.00
	2	1737		3046.459375	0.570	0.59888	3,000	222.5690	0.59888	1,804	66.527	66.5270	42999.64823	176.06885	3.83000	8.26190	2.00
	3	2412	3575	3273.315257	0.737	0.69757	3,246	224.9164	0.69757	2,248	-163.743	163.7432	37603.70970	171.96030	6.78869	7.77083	1.10
	4	7269	3783.75	3500.17114	2.077	1.80029	3,528	230.5795	1.80029	6,249	-1019.522	1019.5224	288059.28326	383.85083	14.02562	9.33453	-2.17
2	5	3514	3965.375	3727.027022	0.943		3,773	232.0694	0.89000	3,345	-168.860	168.8602	236150.18318	340.85272	4.80536	8.42869	-2.93
	6	2143	4069.625	3953.882904	0.542		3,963	227.7976	0.59700	2,391	248.315	248.3148	207068.52307	325.42973	11.58725	8.95512	-2.31
	7	3459	4118.75	4180.738787	0.827		4,267	235.4777	0.70200	2,942	-517.176	517.1762	215697.48612	352.82208	14.95161	9.81176	-3.60
	8	7056	4272.375	4407.594669	1.601		4,445	229.6423	1.82600	8,222	1166.315	1166.3151	358771.67732	454.50872	16.52941	10.65147	-0.23
3	9	4120	4237.375	4634.450551	0.889		4,665	228.7147	0.90200	4,216	96.127	96.1274	319934.87829	414.68858	2.33319	9.72721	-0.02
	10	2766	4274.125	4861.306434	0.569		4,866	225.9649	0.59300	2,902	135.928	135.9276	289789.02285	386.81248	4.91423	9.24592	0.33
	11	2556	4595.125	5088.162316	0.502		4,949	211.6854	0.70900	3,610	1054.303	1054.3027	364494.94654	447.49341	41.24815	12.15521	2.65
	12	8253	4968.5	5315.018199	1.553		5,103	205.9180	1.77900	9,181	928.410	928.4102	405949.15311	487.56981	11.24937	12.07972	4.33
4	13	5491	5390.375	5541.874081	0.991		5,389	213.8857	0.89800	4,768	-723.303	723.3026	414965.88830	505.70310	13.17251	12.16378	2.75
	14	4382	6083	5768.729963	0.760		5,774	231.0281	0.59600	3,339	-1042.730	1042.7302	462988.77411	544.06218	23.79576	12.99464	0.64
	15	4315	6575.375	5995.585846	0.720		6,023	232.8332	0.67900	4,078	-237.432	237.4322	435881.12516	523.62018	5.50248	12.49516	0.21
	16	12035	6509.25	6222.441728	1.934		6,299	237.1222	1.78200	11,148	-886.562	886.5618	457763.04388	546.30403	7.36653	12.17462	-1.42
5	17	5648	6489.5	6449.29761	0.876		6,511	234.5665	0.91100	5,954	306.433	306.4327	436359.39444	532.19395	5.42551	11.77762	-0.89
	18	3696	6688.25	6676.153493	0.554		6,688	228.8306	0.61500	4,148	452.273	452.2735	423481.16786	527.75393	12.23684	11.80313	-0.04
	19	4843		6903.009375	0.702		6,919	229.0910	0.69900	4,835	-8.275	8.2745	401196.28891	500.41291	0.17086	11.19090	-0.05
	20	13097		7129.865257	1.837		7,161	230.3571	1.81100	12,946	-151.380	151.3804	382282.27595	482.96128	1.15584	10.68915	-0.37
6	21								0.81000	5,987			Standard Deviation=	603.70		TSmin	(3.60)
	22								0.53900	4,108						TSmax	4.33
	23								0.62800	4,931							
	24								1.62100	13,102						alpha	0.10
7	25								0.81000	6,733						beta	0.10
	26								0.53900	4,605						gamma	0.10
	27								0.62800	5,510							
	28								1.62100	14,595						Slope	226.85588
																Intercept	2592.74761

Figure 14: Winter's method worksheet.

The *Winter's method* Excel chart is formatted as follows:

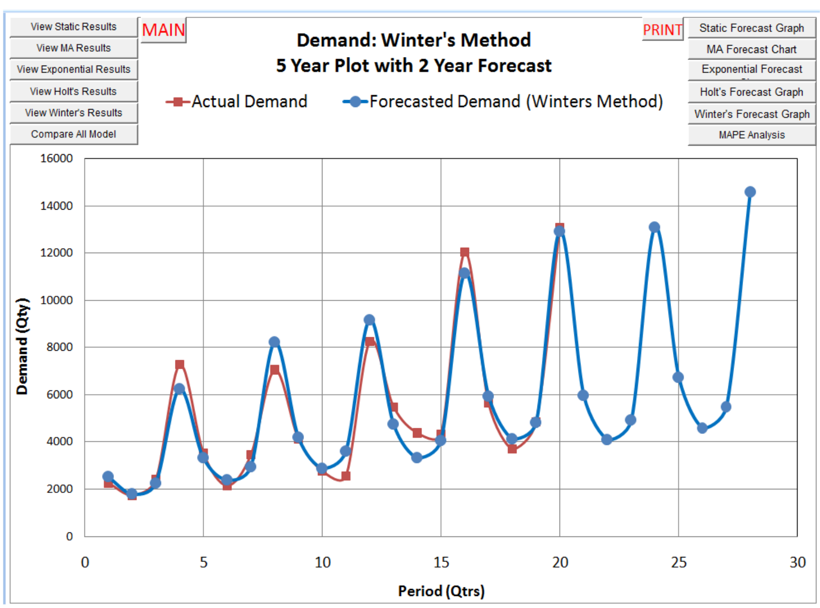


Figure 15: Winter's method chart.

3.1.7 Forecasting Error Analysis

For each forecasting method, it is important to perform an error analysis over the total number of periods, n. The step-wise analytical process is provided below:

Step 1: Compute the Error, E_i, $(i = 1, 2, \ldots, n)$:

$$E_i = F_i - D_i \tag{3.24}$$

$$F_i \triangleq \text{forecast of demand at period } i$$

$$D_i \triangleq \text{actual demand at period } i.$$

Step 2: Compute the mean square error, $(MSE)_n$, $(i = 1, 2, \ldots, n)$:

$$(MSE)_n \triangleq \frac{1}{n}\sum_{i=1}^{n}(E_i)^2. \tag{3.25}$$

Step 3: Compute the absolute error (or deviation), $|E_i|$, $(i = 1, 2, \ldots, n)$:

$$A_i = |E_i| \triangleq |F_i - D_i|. \tag{3.26}$$

Step 4: Compute the mean absolute deviation, $(MAD)_n$, $(i = 1, 2, \ldots, n)$:

$$(MAD)_n \triangleq \frac{1}{n}\sum_{i=1}^{n}A_i = \frac{1}{n}\sum_{i=1}^{n}|E_i| = \frac{1}{n}\sum_{i=1}^{n}|F_i - D_i|. \tag{3.27}$$

Step 5: Compute the mean absolute percent error, $(MAPE)_n(\%)$, $(i = 1, 2, \ldots, n)$:

$$(MAPE)_n \triangleq \frac{1}{n}\sum_{i=1}^{n}\left|\frac{E_i}{D_i}\right| * 100\%. \tag{3.28}$$

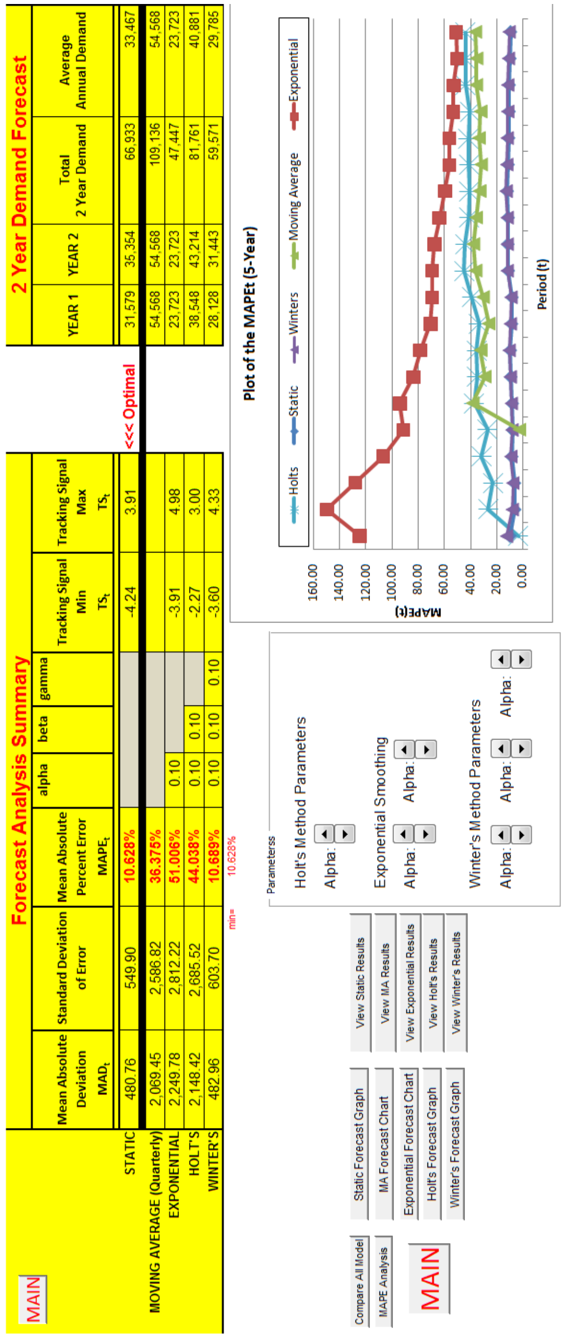
Step 6: Compute the bias, $(Bias)_n$, $(i = 1, 2, \ldots, n)$:

$$(Bias)_n \triangleq \sum_{i=1}^{n}E_i. \tag{3.29}$$

Step 7: Compute the tracking signal, $(TS)_n$, $(i = 1, 2, \ldots, n)$:

$$(TS)_n \triangleq \frac{(Bias)_n}{(MAD)_n}. \tag{3.30}$$

The forecast analysis summary with GUI dashboard and controls excel worksheet is formatted as follows:



Forecast Analysis Summary

	Mean Absolute Deviation MAD_t	Standard Deviation of Error	Mean Absolute Percent Error $MAPE_t$	alpha	beta	gamma	Tracking Signal Min TS_t	Tracking Signal Max TS_t	
STATIC	480.76	549.90	10.628%				-4.24	3.91	<<< Optimal
MOVING AVERAGE (Quarterly)	2,069.45	2,586.82	36.375%						
EXPONENTIAL	2,249.78	2,812.22	51.006%	0.10			-3.91	4.98	
HOLT'S	2,148.42	2,685.52	44.038%	0.10	0.10		-2.27	3.00	
WINTER'S	482.96	603.70	10.689%	0.10	0.10	0.10	-3.60	4.33	
		min=	10.628%						

2 Year Demand Forecast

YEAR 1	YEAR 2	Total 2 Year Demand	Average Annual Demand
31,579	35,354	66,933	33,467
54,568	54,568	109,136	54,568
23,723	23,723	47,447	23,723
38,548	43,214	81,761	40,881
28,128	31,443	59,571	29,785

Figure 16: Forecast analysis summary with GUI dashboard and controls.

3.2 Inventory Management Modeling

The following inventory management modeling use a series of formulas (Desa, 2011; Chopra and Meindl, 2010) to compute the cycle and safety inventory levels. This research work does not explicitly investigate inventory in a supply chain network; however, a software-module was developed to perform inventory based computations utilizing VBA in Excel. Therefore, for purely instructional reasons, the information is presented in this thesis to instruct on the process to automate inventory formulations in a GUI. The details of the implementation process are provided in Section 4.4.

$$
\begin{aligned}
&Notation: \\
D &\triangleq \text{average annualized demand (units)} \\
\sigma_w &\triangleq \text{standard deviation of the demand (weekly)} \\
\mu &\triangleq \text{average demand(units)} \\
CV &\triangleq \frac{\sigma}{\mu} \text{ coefficient of variation} \\
(CV)_D &\triangleq \text{coefficient of variation of demand} \\
(CV)_S &\triangleq \text{coefficient of variation of supply} \\
CSL &\triangleq \text{cycle service level(\%)} \\
ROP &\triangleq \text{reorder point (units)} = ss + D_w L \\
f_R &\triangleq \text{fill rate(\%)} \\
ss &\triangleq \text{safety inventory} = F_s^{-1}(CSL)\sigma_L \text{ (units)} \\
ESC &\triangleq \text{expected shortage per replenishment cycle} \\
D_w &\triangleq \text{average weekly demand (units)} \\
L &\triangleq \text{average lead-time for replenishment (weeks)} \\
D_L &\triangleq \text{demand during lead-time} \\
\sigma_w &\triangleq \text{standard deviation of weekly } D \text{ (units)} \\
\sigma_L &\triangleq \text{standard deviation of } D \text{ during lead-time (units)} \\
n &\triangleq \text{number of shipments on an annualized basis} \\
Q_L &\triangleq \text{lot size} \\
{Q_L}^* &\triangleq \text{optimal lot size} \\
F_z^{-1}(p) &\triangleq \text{inverse of the normalized normal distribution function}
\end{aligned}
$$

The formulas for inventory management are as follows:

$$\text{Optimal Lot Size, } {Q_L}^* \triangleq \sqrt{\frac{2DS}{hC}}. \tag{3.31}$$

$$\text{Cycle Inventory} \triangleq \frac{Q^*}{2}. \tag{3.32}$$

$$\text{Number of order per year} \triangleq \frac{D}{Q^*}. \tag{3.33}$$

$$\text{Annual ordering and holding cost} \triangleq \frac{D}{Q^*}S + \frac{Q^*}{2}hC. \tag{3.34}$$

$$\text{Number of shipments, } n \triangleq \sqrt{\sum_{i=1}^{N} \frac{D_i h C_i}{2S^*}}. \tag{3.35}$$

$$\text{Cost per shipment, } S \triangleq \frac{hC(Q^*)^2}{2D}. \tag{3.36}$$

$$\text{Annual holding costs} \triangleq \frac{D_A h C_A}{2n} + \frac{D_B h C_B}{2n} + \frac{D_C h C_C}{2n}, \tag{3.37}$$

where A, B, C represent three different possible suppliers.

$$\text{Total annual ordering \& holding cost} \triangleq (S * n) + \frac{D_A h C_A}{2n} + \frac{D_B h C_B}{2n} + \frac{D_C h C_C}{2n}, \tag{3.38}$$

where A, B, C represent three different possible suppliers.

$$\text{Safety stock inventory, } ss \triangleq F_z^{-1}(CSL)\sigma_D. \tag{3.39}$$

$$\text{Safety stock inventory, } ss \triangleq F_z^{-1}(CSL)\sigma_D. \tag{3.40}$$

Excel Version:

$$= NORMSINV(CSL)\sigma_L \qquad .$$

$$\text{Expected shortage per cyclce, } ESC \triangleq (1 - f_R)Q_L \tag{3.41}$$

$$= -ss\Big[1 - F_z\Big(\frac{ss}{\sigma_L}\Big)\Big] + \sigma_L f_z\Big(\frac{ss}{\sigma_L}\Big). \tag{3.42}$$

Excel Version:

$$= -ss\Big[1 - NORMDIST\Big(\frac{ss}{\sigma_L}, 0, 1, 1\Big)\Big] + \sigma_L NORMDIST\Big(\frac{ss}{\sigma_L}, 0, 1, 0\Big).$$

$$\text{Reorder point, } ROP \triangleq ss + DL. \tag{3.43}$$

To define a quantitative measure of probability for product availability (supply), we use Cycle Service Level, CSL, which defines the probability, P, of D_L between $-\infty$ and the ROP, by the formulation:

$$CSL \triangleq P\{-\infty < D_L < ROP\}, \tag{3.44}$$

where D_L is the average demand during the lead time, L. With this information, a probability density function (Gaussian curve) can be constructed to represent the relationships of equations.

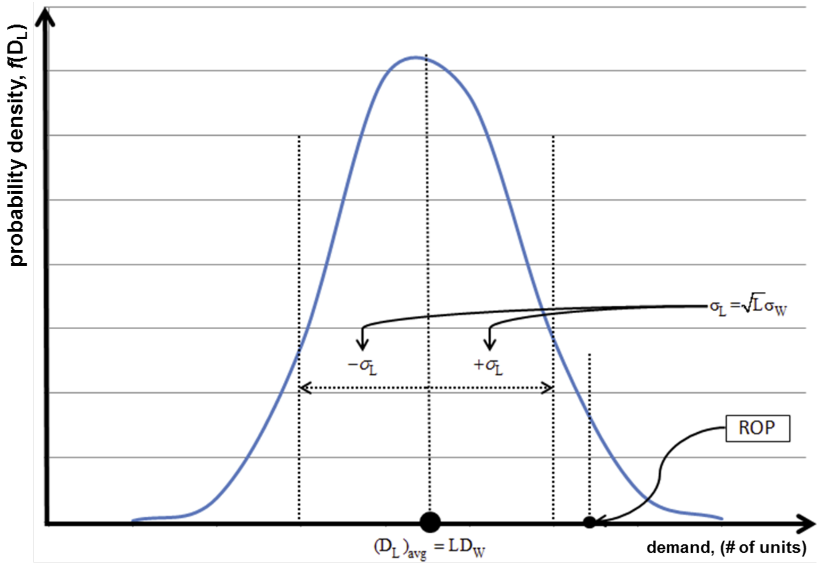


Figure 17: An example of the standard normal probability density function.

The plot in Figure 17 represents the relationship when demand during lead time, D_L, is less than the reorder point, ROP, in terms of the $F_z(z)$. The probability of $D_L < ROP$ is referred to as the Cycle Service level, (CSL). The subscript, z, indicates a normalized distribution function, with $z = {}^{x-\overline{x}}/_{\sigma}$, at $\overline{x}$, $z = 0$. The origin is defined by the mean, $\mu \equiv \overline{x}$, and the measure of distance is defined by σ = standard deviation from the mean. In our work, the coefficient of variation of demand, defined as the ${}^{\sigma}/_{\mu}$ is used to investigate the required responsive of the supply to meet demand is meeting.

The integration of the normal probability density function, $f_z(z)$, yields the probability distribution function, $F_z(z)$, formulated as:

$$F_z(z) = \int_{-\infty}^{z} f_z(z)dz, \tag{3.45}$$

and the relationship of the CSL and the $F_z(z)$ shows that:

$$\begin{aligned} CSL &= \rho(D_L < ROP) \equiv \rho(-\infty < D_L < ROP) \\ &= F(ROP) - F(-\infty), F(-\infty) \to 0 \\ &= F(ROP, (D_L)_{avg}, \sigma_L) \\ &\quad (D_L)_{avg} = LD_w, \sigma_L = \sqrt{L}\sigma_w \\ &= F(ROP, LD_w, \sqrt{L}\sigma_w), \\ \therefore CSL &= F(ROP, LD_w, \sqrt{L}\sigma_w). \end{aligned} \tag{3.46}$$

In the $F_z(z)$ of the probability distribution function, the z is defined as:

$$z = \frac{(x - \overline{x})}{\sigma} = \frac{ROP - (D_L)_{avg}}{\sigma_L}. \tag{3.47}$$

The expression for the CSL is formulated as:

$$CSL = F_z\Big[z = \frac{ROP - (D_L)_{avg}}{\sigma_L}, \mu = 0, \sigma = 1\Big]. \tag{3.48}$$

The normalized distribution has an origin with a mean value, $\mu = 0$, and a measure of distance with a standard deviation, $\sigma = 1$. Utilizing the statistical Z-Tables, it is possible to convert the z value to a probability value. Therefore, the demand uncertainty, in terms of supply, can be defined by the measure of the CSL:

$$CSL = F_z\Big[z = \frac{ROP - (D_L)_{avg}}{\sigma_L}, \mu, \sigma\Big]. \tag{3.49}$$

Condensing the formulation yields:

$$CSL = F_z\Big[\frac{ss}{\sigma_L}, \mu, \sigma\Big]; ss \triangleq ROP - D_L, \mu = 0, \sigma = 1. \tag{3.50}$$

$$CSL = F_z\left[\frac{ss}{\sigma_L}, \mu, \sigma\right]; ss \triangleq ROP - (D_L)_{avg}, \mu = 0, \sigma = 1\Big]. \tag{3.51}$$

To solve for the ss requires an inverse procedure, $F_z^{(-1)}$, which states that "given a probability, p, the $F_z^{(-1)}(p, \mu, \sigma)$ is the value of x such that p is the probability that the normal random variable takes on x or less" (Chopra and Meindl, 2010, pg. 324).

Rearranging the terms:

$$\frac{ss}{\sigma_L} = F_z^{-1}(CSL). \tag{3.52}$$

Substituting for the ss:

$$\frac{ROP - (D_L)_{avg}}{\sigma} = F_z^{-1}(CSL), \tag{3.53}$$

and rearranging the terms for the re-order point, in terms of demand of uncertainty for a desired CSL, is formulated as:

$$ROP = (D_L)_{avg} + F_z^{-1}(CSL)\sigma_L. \tag{3.54}$$

With a computed σ_L, two equations are established for a direct and indirect approach to compute the safety inventory for a desired CSL:

Direct

$$CSL = F_z\left[z = \frac{ROP - (D_L)_{avg}}{\sigma_L}, \mu, \sigma\right] \tag{3.55}$$

$$\mu = 0, \sigma = 1$$

Indirect

$$\frac{ss}{\sigma_L} = F_z^{-1}(CSL). \tag{3.56}$$

Computing the σ_L from the demand forecast and setting a desired CSL, the safety stock, ss, can be derived.

$$\text{Cycle Service Level}, CSL \triangleq F(ROP, D_L, \sigma_L).$$

$$\text{Excel Version:}$$

$$= NORMDIST(ROP, D_L, \sigma_L, 1). \tag{3.57}$$

$$\text{Standard deviation of demand during lead-time}, \sigma_L \triangleq \sqrt{L(\sigma_D^2) + D^2(s_L^2)}. \tag{3.58}$$

Next, it is possible to compute the $TotalAnnualCost$:

$$\text{Total Annual Cost}, TC \triangleq CD + \frac{D}{Q}S + \frac{Q}{2}hC. \tag{3.59}$$

Lastly, it is understood that in order to compute optimal order quantity, Q_L^*, one needs to compute the first derivative of the TC function and setting it equal to zero and solving for Q_L^*:

$$\begin{aligned} \frac{\partial(TC)}{\partial(Q_L)} &= 0 + -\Big(\frac{D}{Q_L^2}\Big)S + \frac{1}{2}hC \\ \text{set } \frac{\partial(TC)}{\partial(Q_L)} &= 0 \text{ and solve for } Q_L^* \\ Q_L^* &= \sqrt{\frac{2DS}{hC}}. \end{aligned} \tag{3.60}$$

All of the inventory formulations are translated into VBA code within the *Appendix: VBA Code for the Modules in Section 7*

3.3 Supply Chain Network Modeling

3.3.1 Overview of the supply chain network

In our work various forms of supply networks, as discussed by Tsiakis et al. (2001), Chopra and Meindl (2010), Ferreira (2009), Ding et al. (2007), Peidro et al. (2009), Persson and Olhager (2002), Persson and Olhager (2002), Snyder (2006), and You and Grossmann (2010), were examined to develop our facilities location networking model. The related works are divided into two categories:

1. Two-stage networks

2. Multi-echelon networks

and are discussed in the following sections.

3.3.2 Two-stage supply chain network

In Figure 18 is shown the network view of the two-stage supply chain network, including manufacturers and distributors.

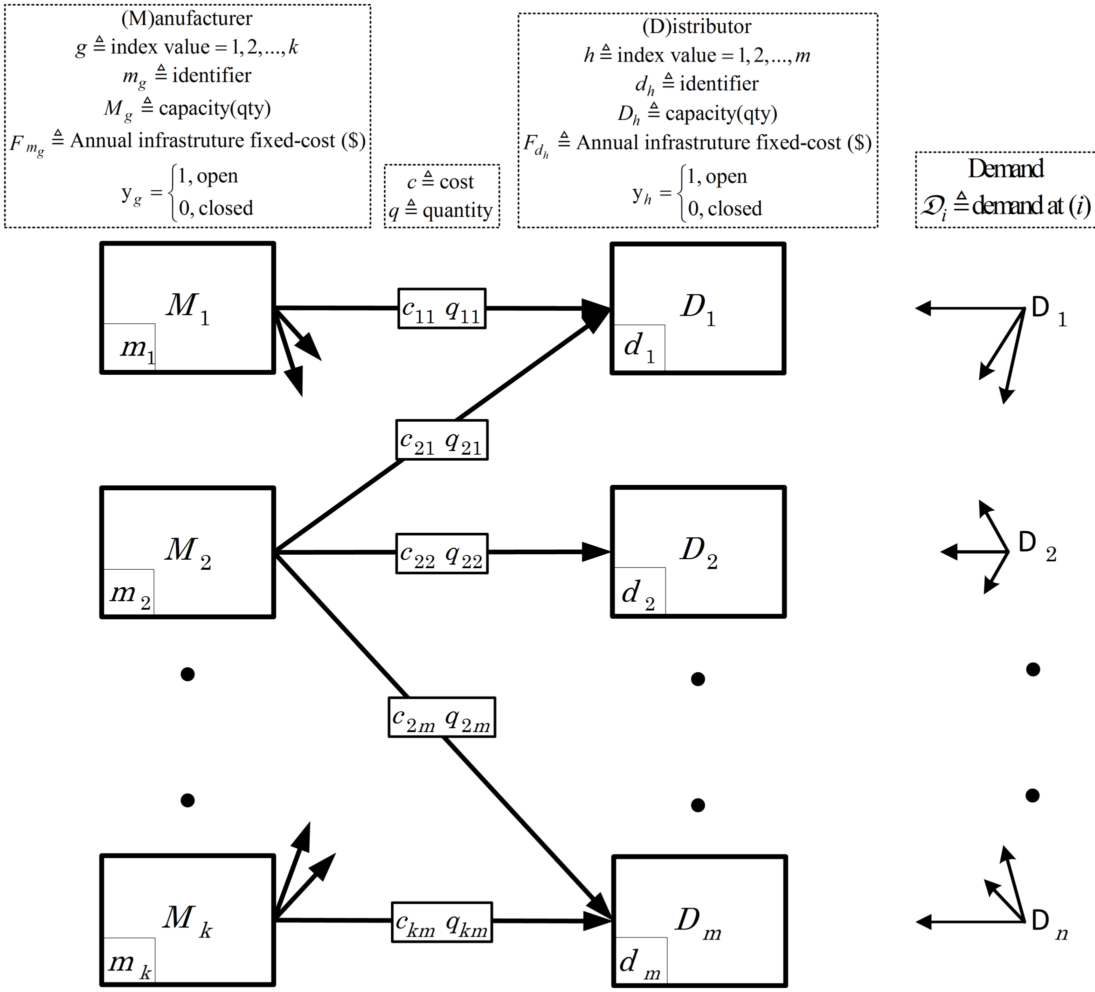


Figure 18: View of the two-stage supply chain network.

The two-stage network is reformulated in our notation:

$$
\begin{array}{rl}
\multicolumn{2}{l}{Notation:} \\
g & \triangleq \text{index for manufacturer locations} \\
h & \triangleq \text{index for distributor locations} \\
k & \triangleq \text{number of manufacturer locations} \\
m & \triangleq \text{number of distributor locations} \\
m_g & \triangleq \text{manufacturer } g \\
M_g & \triangleq \text{capacity at manufacturer plant } g \\
F_{m_g} & \triangleq \text{annual fixed infrastructure cost(\$) at manufacturer } g \\
d_h & \triangleq \text{distributor h} \\
D_h & \triangleq \text{capacity at distributor site } h \\
\mathfrak{D}_i & \triangleq \text{annual demand for market } i \\
c_{gh} & = \text{cost(\$)of producing and shipping one unit} \\
 & \quad\quad \text{from manufacturer } g \text{ to distributor } h \\
 & \quad\quad \text{cost includes production, inventory} \\
 & \quad\quad \text{transportation and tariffs.} \\
q_{gh} & \triangleq \text{quantity shipped from manufacturer } g \text{ to distributor } h \\
y_g & = \begin{cases} 1 & \text{if manufacturer located at site } g \text{ is open} \\ 0 & \text{otherwise} \end{cases} \\
TC & \triangleq \text{total overall cost(\$) of the supply chain network}
\end{array}
$$

$$\underset{TC}{\text{Minimize}} \left[\sum_{g=1}^{k} F_{m_g} y_g + \sum_{g=1}^{k} \sum_{h=1}^{m} c_{gh} q_{gh} \right], \tag{3.61}$$

$$\text{subject to} \tag{3.62}$$

$$
\begin{aligned}
& M_g y_g - \sum_{h=1}^{m} q_{gh} \geq 0 \text{ for } g = 1, \ldots, k, \\
& \sum_{i=1}^{n} \mathfrak{D}_i - \sum_{h=1}^{m} q_{gh} = 0 \text{ for } g = 1, \ldots, k. \\
& y_g \in \{0, 1\}, q_{gh} \geq 0.
\end{aligned}
$$

3.3.3 Multi-echelon supply chain networks

In Figure 19 is shown the network view of the multi-echelon supply chain network, including suppliers, manufacturers, distributors and retailers.

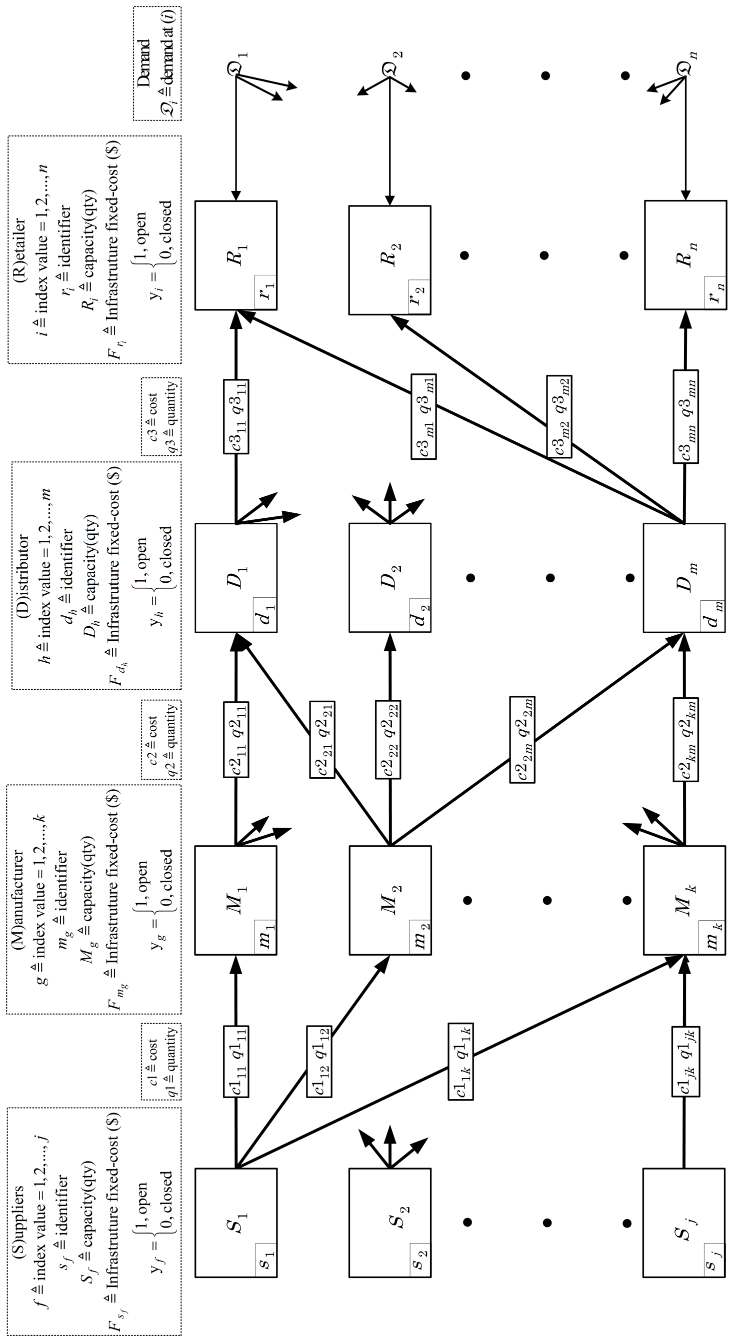


Figure 19: View of the multi-echelon supply chain network.

The multi-echelon facility location problems is reformulated in our notation:

g	$\triangleq$	index for manufacturer locations
h	$\triangleq$	index for distributor locations
i	$\triangleq$	index for market locations
r	$\triangleq$	index for retail locations
s	$\triangleq$	index for supplier locations
j	$\triangleq$	number of suppliers
k	$\triangleq$	number of manufacturers
m	$\triangleq$	number of distributors
n	$\triangleq$	number of retailers (demand points)
s_f	$\triangleq$	supplier f
S_f	$\triangleq$	capacity at supplier f
F_{s_f}	$\triangleq$	annual fixed infrastructure cost($) of locating a plant at supplier site f
m_g	$\triangleq$	manufacturer g
M_g	$\triangleq$	capacity at manufacturer plant g
F_{m_g}	$\triangleq$	annual fixed infrastructure cost($) of locating a plant at manufactuer site g
d_h	$\triangleq$	distributor h
D_h	$\triangleq$	capacity at distributor site h
F_{d_h}	$\triangleq$	annual fixed infrastructure cost($) of locating a plant at distributor site h
r_i	$\triangleq$	retailer i
R_i	$\triangleq$	capacity at retailer site i
F_{r_i}	$\triangleq$	annual fixed infrastructure cost($) of locating a plant at retailer site i
$\mathfrak{D}_i$	$\triangleq$	annual demand for market i
$c1_{fg}$	$\triangleq$	total cost($) of one unit from supplier f to manufactuer g
$c2_{gh}$	$\triangleq$	total cost($) of one unit from manufactuer g to distributor h.
$c3_{hi}$	$\triangleq$	total cost($) of one unit from distributor h to retailer i.
$q1_{fg}$	$\triangleq$	quantity shipped from supplier f to manufacturer g
$q2_{gh}$	$\triangleq$	quantity shipped from manufacturer g to distributor h
$q3_{hi}$	$\triangleq$	quantity shipped from distributor h to retailer i
TC	$\triangleq$	total overall cost($) of the supply chain network.
		<u>decision variables</u>
y_f	$=$	$\begin{cases} 1, & \text{if supplier located at site } f \text{ is open} \\ 0, & \text{otherwise} \end{cases}$
y_g	$=$	$\begin{cases} 1, & \text{if manufacturer located at site } g \text{ is open} \\ 0, & \text{otherwise} \end{cases}$
y_h	$=$	$\begin{cases} 1, & \text{if distributor located at site } h \text{ is open} \\ 0, & \text{otherwise} \end{cases}$
y_i	$=$	$\begin{cases} 1, & \text{if retailer located at site } i \text{ is open.} \\ 0, & \text{otherwise} \end{cases}$

Table 1: Table of notation for multi-echelon supply chain network.

$$\underset{TC}{\text{Minimize}} \Bigg[\underbrace{\sum_{f=1}^{j} F_{s_f} y_f + \sum_{g=1}^{k} F_{m_g} y_g + \sum_{h=1}^{m} F_{d_h} y_h + \sum_{i=1}^{n} F_{r_i} y_i +}_{\text{annual fixed infrastructure costs}} \tag{3.63}$$

$$\underbrace{\sum_{f=1}^{j}\sum_{g=1}^{k} c1_{fg} q1_{fg} + \sum_{g=1}^{k}\sum_{h=1}^{m} c2_{gh} q2_{gh} + \sum_{h=1}^{m}\sum_{i=1}^{n} c3_{hi} q3_{hi}}_{\text{product flow cost}}\Bigg],$$

subject to (3.64)

$$S_f y_f - \sum_{g=1}^{k} q1_{fg} \geq 0 \text{ for } f = 1, \ldots, j, \tag{3.65}$$

$$\sum_{f=1}^{j} q1_{fg} - \sum_{h=1}^{m} q2_{gh} \geq 0 \text{ for } g = 1, \ldots, k, \tag{3.66}$$

$$M_g y_g - \sum_{h=1}^{m} q2_{gh} \geq 0 \text{ for } g = 1, \ldots, k, \tag{3.67}$$

$$\sum_{g=1}^{k} q2_{gh} - \sum_{i=1}^{n} q3_{hi} \geq 0 \text{ for } h = 1, \ldots, m, \tag{3.68}$$

$$D_h y_h - \sum_{i=1}^{n} q3_{hi} \geq 0 \text{ for } h = 1, \ldots, m, \tag{3.69}$$

$$\sum_{i=1}^{n} \mathfrak{D}_i - \sum_{h=1}^{m} q3_{hi} = 0 \text{ for } i = 1, \ldots, n, \tag{3.70}$$

and

$$y_f, y_g, y_h, y_i \in \{0, 1\}, q1_{fg}, q2_{gh}, q3_{hi} \geq 0. \tag{3.71}$$

3.4 The Integrated Hierarchical Framework

3.4.1 A Hierarchical view of Handling Uncertainty

Shown in Figure 20 is the two-level hierarchical framework our work develops to address uncertainty, consisting of: high-level, macro scenario planning and low-level, micro Monte Carlo simulation approaches.

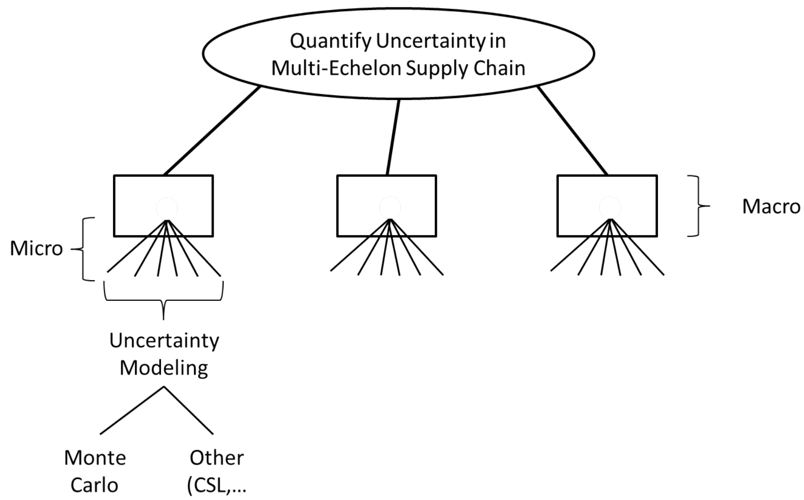


Figure 20: Quantifying uncertainty in a multi-echelon supply chain network design.

In the following sections, we discuss the theory of the framework components (Section 3.4.2) and the integration process (Section 3.4.3).

3.4.2 Theory of Macro and Micro Level Framework Components

In our framework, the two components for addressing uncertainty are:

(1) Macro level: scenario planning

A macro level process for handling uncertainty, such as scenario planning (Schoemaker, 1995, 1991; Vanston et al., 1977) is used in risk analysis because it considers a wide range of possible future outcomes. Other macro level approaches include: what-if analysis and sensitivity analysis. In this work, we utilize the scenario planning process which carefully considers the key uncertainties of the stakeholders.

The scenario planning approach (Vanston et al., 1977) considers and consolidates the key uncertainties that are most relevant to the stakeholders into a small quantity of manageable scenarios.

The construction of the scenarios, discussed in Section 3.4.3, follows a structured process for scenario planning (Vanston et al., 1977; Schoemaker, 1995) and from a discussion with Chao (2012) of Seagate, Inc to understand key uncertainties involved with supply chain management of high-tech products.

(2) Micro level: Monte Carlo simulation

A micro level process, such as Monte Carlo, is useful for considering a range of possible outcomes, but is limited to only a specific situation. In our work, the Monte Carlo method is used for repeated statistical-based experiments, using computer-based simulations, to help approximate solutions to a supply chain network design problem. In general terms, a computer simulation is a process for building a model of an uncertain system and then performing repeated numerical analysis to understand the statistical significance of the underlying system.

The Monte Carlo method is based on sampling random variables, X, from the cumulative distribution function, $F(x)$, denoted by (Hillier and Lieberman, 2005, pg. 951):

$$F(x) = P\{X \leq x\}, \tag{3.72}$$

where $P\{X \leq x\}$ is the probability of $X \leq x$.

In our work, the Monte Carlo simulation generates random variables, X, which are derived from a normal probability distribution, to represent average annual regional demand. Shown in Figure 21, X is a random variable that has a cumulative distribution function, $F(x)$, and y, denoting a uniformly distributed random number in which $0 \leq y \leq 1$. The relationships of y and X are illustrated in Figure 21.

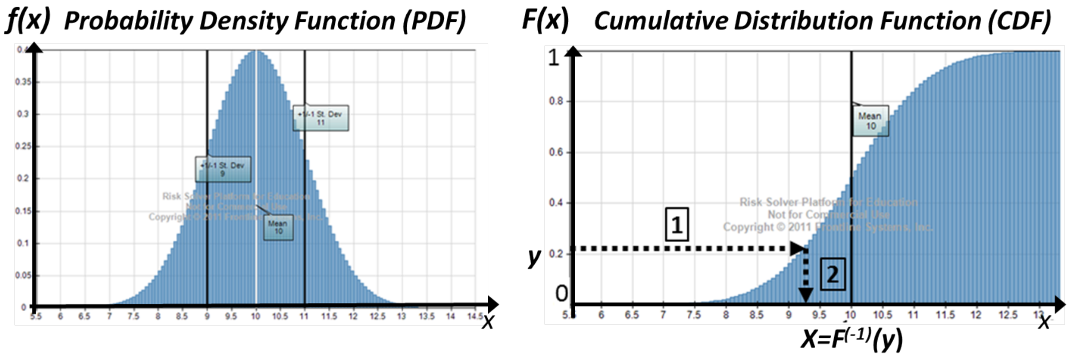


Figure 21: The cumulative distribution function (CDF) and the relationship to a random variable, X.

The sampling for the numerical analysis requires that variables in the simulation model originate as independent random independent, that correspond to a dependent output value, through an associated probability distribution (e.g, normal distribution). The normalization of the distribution function allows us to declare that the area under the curve is a unique number between 0 and 1. Then using a pseudo random number generator (e.g., CMRG) we choose values between 0 and 1 and attain a number, y. The random inputs (independent values), which are uniformly distributed numbers between an interval of [0,1], are used to generate the stochastic output variables (dependent values). The repeated sampling between 0 and 1 creates a stochastic simulation (a probabilistic system that is changing over time) to model the behavior of the system (Hillier and Lieberman, 2005). To automate the repeated sample, the Monte Carlo simulation is performed using software (Ragsdale, 2011) to automate the process.

To generate a random number, pick a value, y, between 0 to 1, $0 \leq y \leq 1$, and plot this value on the vertical $F(x)$ axis. Next move horizontally (represented by [1] on Figure 21) until reaching the distribution function curve, at which point the corresponding X variable is attained on the horizontal axis (represented by [2] on Figure 21). Restated, the random variable, X, is generated by the inverse function method with a given distribution, $X = F^{(-1)}(y)$. This approach can be utilized with other known distributions (e.g, discrete uniform, Poisson, binomial, geometric, Hypergeometric) and continuous distributions (e.g., uniform, normal, exponential, beta, gamma, weibull, log-normal, chi-square, student's t, and F-distribution). In our work we use the normal distribution, which is defined by:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} exp\Big[-\frac{1}{2}\Big(\frac{x-\mu}{\sigma}\Big)^2\Big], (-\infty < x < \infty). \tag{3.73}$$

To summarize the Monte Carlo method in a step-wise process:

Setup:

(a) Define the normal distribution function with a mean, μ, and standard deviation, σ, to create the plot of the probability density function, PDF.

(b) Normalize the normal distribution function to create the cumulative distribution function, CDF.

Simulation: Perform N random trials (e.g., $N = 10,000$) as follows:

(a) For each trial, generate a random number, y, between 0 and 1 on the vertical axis, $F(x)$, of the CDF. Set $F(x) = y$.

(b) Use y to determine the corresponding X value from the CDF, $X = F^{(-1)}(y)$. That is the average annual regional demand quantity.

(c) Apply this demand value into the model.

(d) Collect the results into a table.

(e) Repeat the simulation from step (a) for N trials to generate a new random variable.

In Section 3.4.3 we discuss the process to integrate the framework components.

3.4.3 The Integration Process of the Framework

Our integrated framework addresses uncertainty for a broad spectrum of possible outcomes and provides specific quantified results for the most probable future scenario. In contrast to our work, the research in the related works is divided into two distinct approaches to addressing uncertainty by using the macro, or, the micro approach:

1. Heuristic (macro)(i.e.,Tsiakis et al. (2001))

2. Parametric probability (micro)(i.e.,Junga et al. (2004); Schmitt and Singh (2009))

Shown in Figure 22 are the heuristic and probabilistic approaches of the related works, alongside our integrated framework. In our work, the heuristic and probabilistic approaches are unified into an integrated framework for modeling a multi-echelon supply chain network under the influence of demand uncertainty, for a high tech manufacturer's perspective.

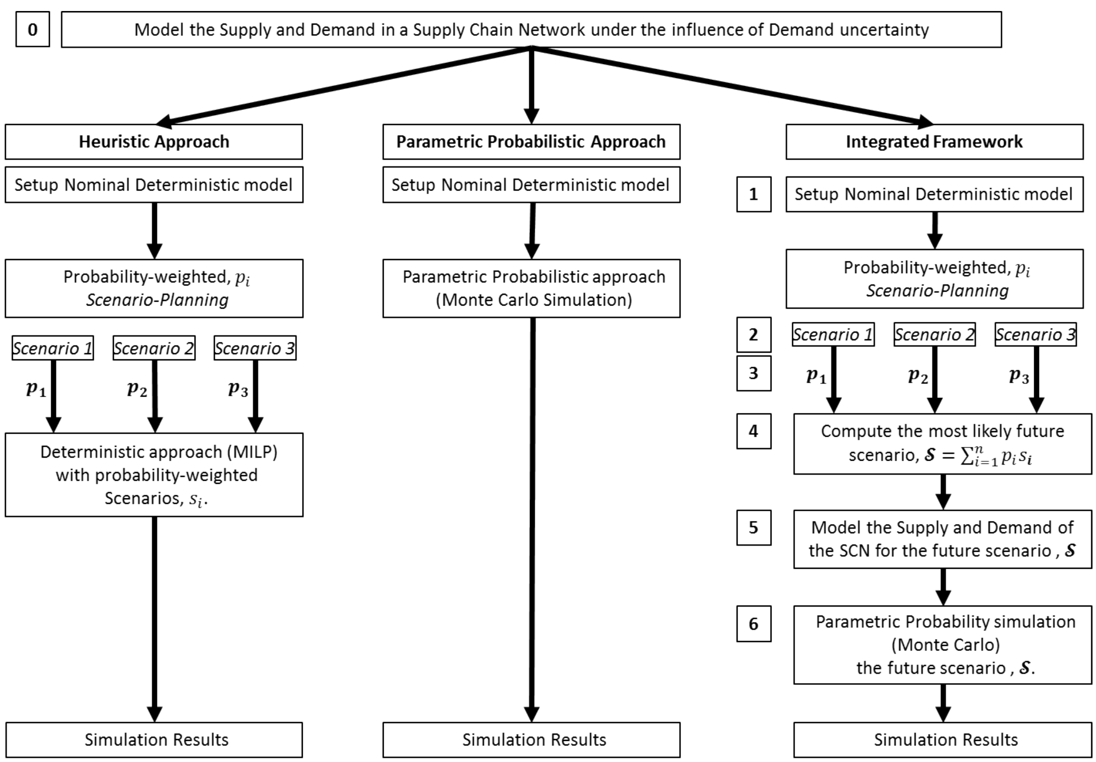


Figure 22: An integrated hierarchical framework.

The macro and micro components are integrated in the following step-wise process:

Step 1: Setup the nominal deterministic model with an objective function to minimize total cost.

Step 2: Scenario planning is used a method to generate and consolidate key stakeholder uncertainties into three possible scenarios: a nominal scenario and two alternative scenarios using the following step-wise approach:

(a) Stakeholder's must identify the key uncertainties that describe the breadth of unknowns encompassing the supply chain network.

(b) Build a correlation matrix to establish the positive, +, and negative, -, relationships between the uncertainties.

	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**
U1		-	-	-	+	+	-
U2			-	+	+	+	-
U3				+	+	+	+
U4					+	+	-
U5						+	+
U6							-
U7							

$U_{ij} = U_{ji}$

Table 2: Example of a correlation matrix of the seven key uncertainties.

(c) Consolidate the "+" and "-" of the correlation matrix into three scenarios. Group the vertical columns that contain all the "+" relationships to form the "Nominal". Group the horizontal rows that contain only the "+" relationship from both the vertical columns into two groups, creating two more alternate scenarios (e.g., high/low, good/bad).

	U1	**U2**	**U3**	**U4**	**U5**	**U6**	**U7**
U1		-	-	-	+	+	-
U2			-	+	+	+	-
U3				+	+	+	+
U4					+	+	-
U5						+	+
U6							-
U7							

$U_{ij} = U_{ji}$

Table 3: Example of a correlation matrix with the nominal scenarios "+" selected.

(d) The scenarios are named and given descriptions.

Scenario#	**Scenario Name**	**Description**
Scenario 1, s_1	"#1"	The "#1" scenario description.
Scenario 2, s_2	"Nominal"	The "Nominal" scenario description.
Scenario 3, s_3	"#2"	The "#2" scenario description.

Table 4: Scenario planning summary.

Step 3: The scenarios are assigned probabilities, p_i, corresponding to case study configurations.

	Scenario 1 s_1 **Alternate 1**	**Scenario 2** s_2 **Nominal**	**Scenario 3** s_3 **Alternate 2**
Base Case	$p_1 = 33\%$	$p_2 = 33\%$	$p_3 = 33\%$
Case 1	$p_1 = 100\%$	0	0
Case 2	0	$p_2 = 100\%$	0
Case 3	0	0	$p_3 = 100\%$

Table 5: Scenario planning probabilities.

Step 4: Use a decision-analytic approach (Hillier and Lieberman, 2005) and the probability, p_i, of each possible future scenario, s_i, to compute the most likely future scenario, $\boldsymbol{S} = \sum_{i=1}^{n} p_i s_i$.

Step 5: Model the supply chain network and compute a solution which minimizes the total cost objective function, for the most probable future scenario, $\boldsymbol{S}$.

Step 6: Perform a probability parametric analysis (Monte Carlo) on the input value for the regional demand quantity, using a normal distributions function with $\pm 3\sigma$ to define demand uncertainty.

We use the CMRG random number generator to pick values that are then associated with a normal distribution function to attain random variables which represent demand quantity. Each cycle of attaining a random variable is referred to as a trial. In our work, we set automation parameters for each simulation to repeat for 10,000 trials and to repeat the simulation ten times, for a total of 100,000 trials.

Shown Figure 23 are the inputs and outputs of the simulation in our work. The two inputs are the average annual demand, μ_D, and the standard deviation of demand, σ_D. The two outputs are the supply quantity that is needed to fulfill demand and the total cost of the supply chain network.

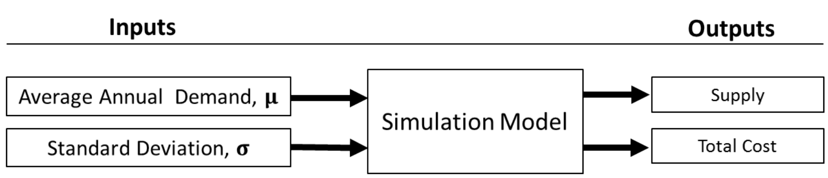


Figure 23: Modeling demand uncertainty in a supply chain network design.

In our work, the inputs we use are the standard deviation of demand value that is a multiplicative value of the μ, defined by: $\sigma_D = \mu * (CV)_D$. The basis for using this formulation of σ is the relationship referred to as the *coefficient of variation*, CV, which is a useful measure to describe the relationship because “it represents the ratio of the standard deviation to the mean for the data sample and describes the relationship, without a dependency on the units-of-measure between the two variables (UCLA ATS Statistical Consulting Group, 2011).” The formulation for CV is defined (Chopra and Meindl, 2010):

$$\text{Coefficient of cariation, } CV \triangleq \frac{\text{standard deviation}}{\text{mean}} = \frac{\sigma}{\mu}. \tag{3.74}$$

Using the CV makes it is possible to compare how the standard deviation, σ, relates to the mean, μ. Our goal is to understand the influence that change in CV of demand, $(CV)_D$, has on the relationship on the two outputs, supply and total cost.

For a Monte Carlo simulation that is based on a normal distribution, the mean,μ, and the standard deviation,σ, are the required input parameters. Our work uses two demand related input values that feed into the normal distribution function:

(a) Average annual demand (regional), μ_D; and

(b) Standard deviation of the average annual demand (regional), σ_D, in the form of $\mu_D * (CV)_D$.

in which the simulation parameters automatically increment the CV_D from .01% to 50%, as shown in Table 6. By increasing the CV_D, we are able to see what happens to the supply and total cost as the standard deviation increases, causing greater fluctuations in the uncertain demand. For the outputs, we quantity the supply that is needed to fullfill the demand and the total cost of the supply chain network design.

Each simulation generates 10,000 trials. The output results of the corresponding variation in supply to meet demand and total cost of the supply

Simulation#	$(CV)_D\%$
Simulation 01	.01%
Simulation 02	05%
Simulation 03	11%
Simulation 04	16%
Simulation 05	22%
Simulation 06	27%
Simulation 07	33%
Simulation 08	38%
Simulation 09	44%
Simulation 10	50%

Table 6: Simulation parameters.

chain network are then analyzed to understand the effect that increasing the coefficient of variation of demand (i.e., increasing the fluctuations of uncertainty) has on the two output values. At the conclusion of the simulation, the average annual demand (regional), μ_D, is incremented by $10,000\frac{units}{region}$, and the simulation repeated up to $50,000\frac{units}{region}$, provided in Table 7.

Analysis#	$\frac{\mu_D}{region}$
1	10,000
2	20,000
3	30,000
4	40,000
5	50,000

Table 7: Average annual demand parameters.

In Section 4 is discussed the step-wise implementation process of the integrated framework to modeling uncertainty in the supply chain network design.

3.5 Dashboard/Cockpit Automation

Shown in Figure 24 is an integrated framework of the architecture for a complete supply chain automation system with four integrated supply chain modules (14, 15, 16, 17) that manage the analytical relationships of each supply chain stage: supplier and factory are (1) and (2), factory and distributor are (3) and 4), distributor and retailers are (5) and (6), retailer to customer are (7) and (8). The data from each stage feeds (9, 10, 11, and 12) into the *optimization and simulation engine* for quantitative processing of the input parameters into the supply chain network model. The *optimization and simulation engine* feeds the quantitative results into the dashboard cockpit (13), which provides a centralized location to change parameters to quickly alter and analyze the output display results. The data flows are bi-directional because the dashboard cockpit allows for changes in parameters to quickly permeate throughout the entire system. The integrated framework is important for facilitating the data entry parameters in a centralized GUI dashboard and presenting the data in a visual graphic interface using a dashboard approach.

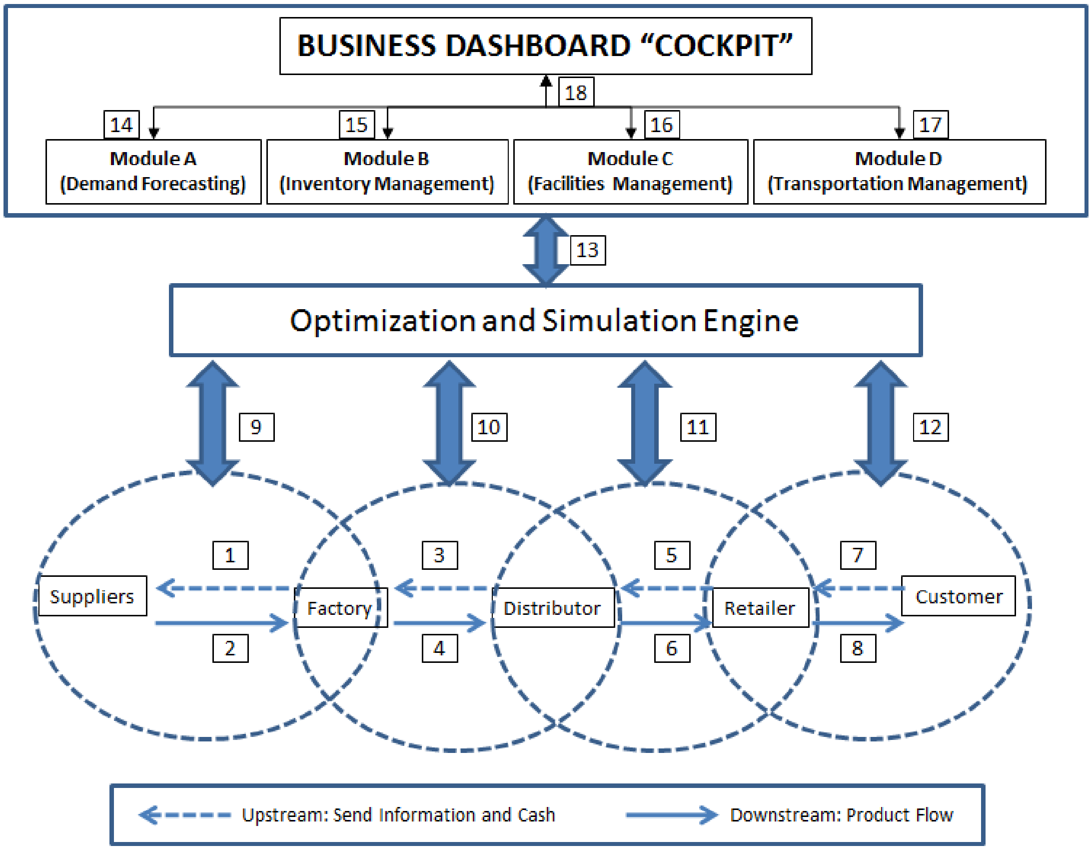


Figure 24: Integrated supply chain network with software automation dashboard.

This work considers and presents a step-wise process to building a software automation platform with Microsoft® Excel with the Risk Solver Platform. The implementation includes the development of the Excel worksheet architecture, VBA code, and the design of a dashboard GUI cockpit to control the automation input parameters.

As shown in Figure 25, our work follows a three step approach to software automation development for rapid simulation:

Step 1: Pre-Processing

Step 2: Processing

Step 3: Post-Processing

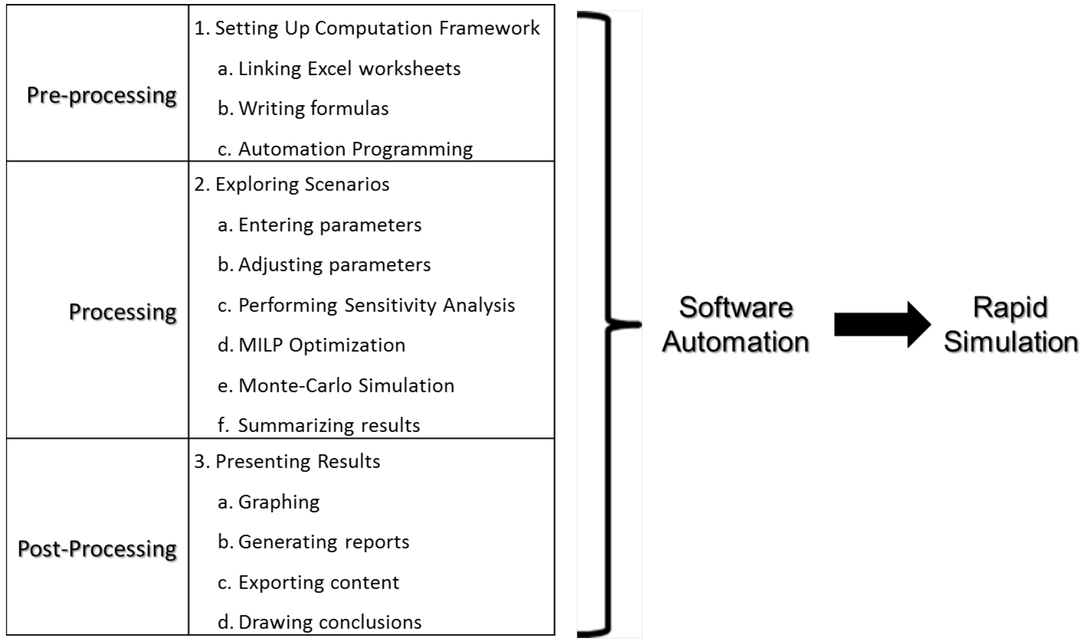


Figure 25: Process for the implementation of software automation for rapid simulation.

The software modules which are important for supply chain management (SCM) are:

Module 1: Demand forecasting

Module 2: Inventory management

Module 3: Facilities Management (Supply Chain Network Design)

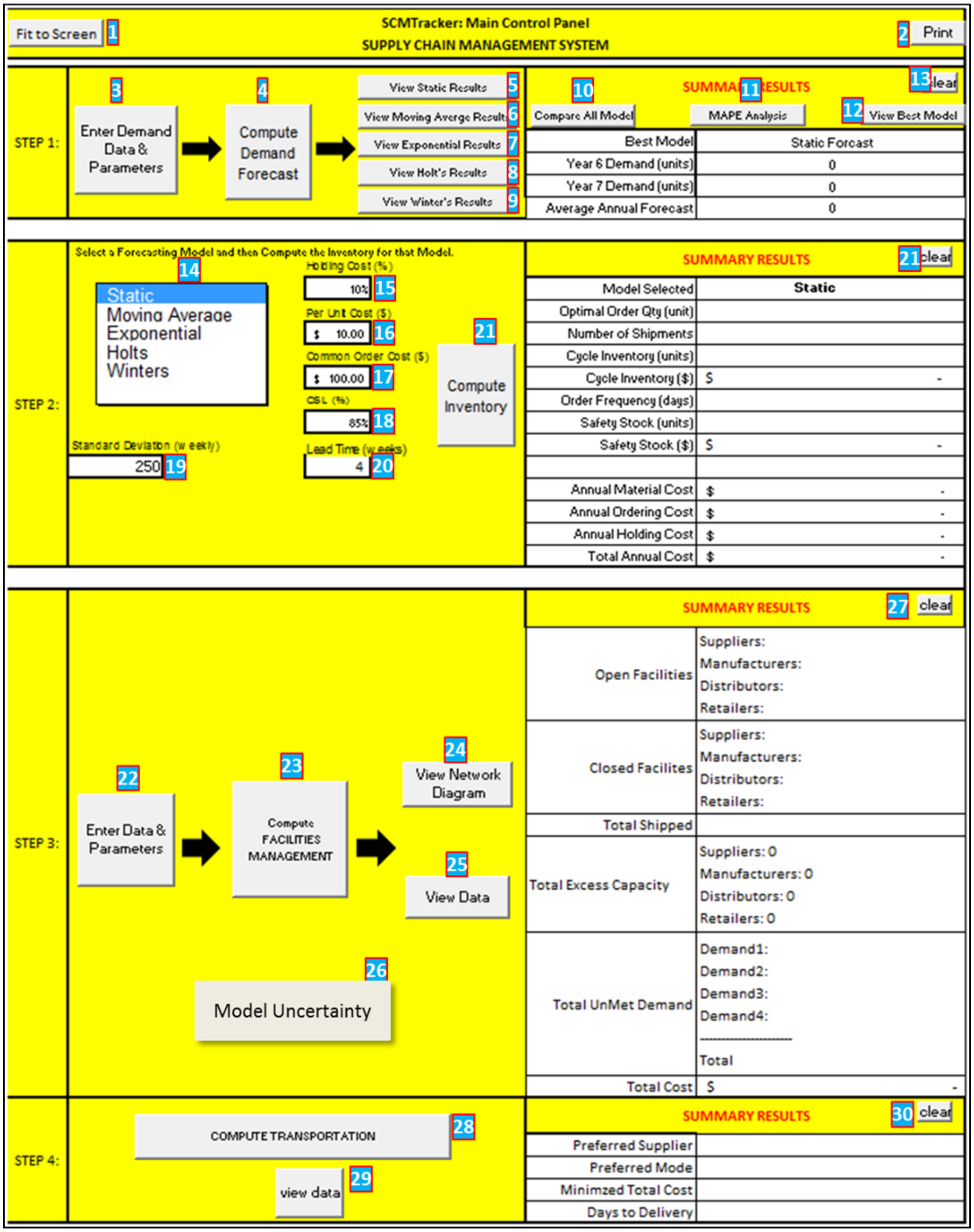


Figure 26: Top level of the software GUI control panel.

This research focuses on only utilizing the *Step 3: Facilities Management* module *(buttons 22, 23, 24, 25 and 26)*, to study and quantify the influence of demand uncertainty on a supply chain network design (SCND). As shown in Figure 24, a complete supply chain management system would contain software modules for quantifying the demand, inventory, facilities, and transportation. This work is primarily focused on the uncertainty in demand and the effect this uncertainty has in the supply chain network on the supply and total cost outcomes. A simple inventory module is developed and provided strictly for instructional purposes on how to program the inventory formulations in VBA and display the results in a main level GUI.

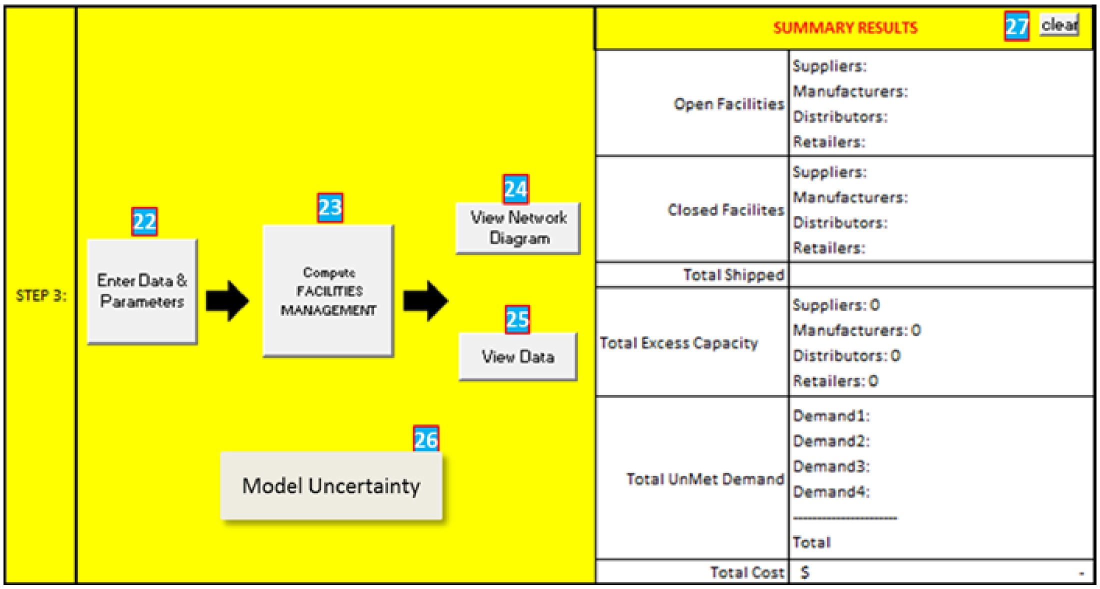


Figure 27: Facilities management software module control panel.

A discussion of the process and formulations for demand forecasting in Section 3.1 and how the result of the forecast, referred to as the average annual demand, $\overline{\mathfrak{D}}$, is used as the input value into the modeling and simulation of the supply chain network design.

Section 4 describes the implementation process of assembling the software automation infrastructure framework using Microsoft® Excel, VBA programming, and Risk Solver Platform with the Monte Carlo simulation software add-in.

4 Implementation

The approach for the implementation of the integrated framework in our work utilizes the following step-wise sequence for building the integrated framework in Microsoft® Excel. There are numerous platform choices (e.g., Matlab, SPSS) to implement the theory discuss in our work. However, our work is pursued in Microsoft® Excel to specifically showcase the process in a business productivity tool that is common to most workplace computer desktops and at the low cost.

Step 1: Scenario planning

Step 2: Configuration of the automation platform: Microsoft® Excel

Step 3: Framework for the demand forecasting analysis module

Step 4: Framework for the inventory analysis module

Step 5: Framework for the facilities management module

- **(1)** Framework for the two-stage capacitated plant
- **(2)** Framework for expanding the multi-echelon capacitated plant
- **(3)** Framework for implementing demand uncertainty into a multi-echelon supply chain network

Step 6: Framework for the transportation management analysis module

Step 7: GUI automation

Step 8: Integrated dashboard architecture

In the next sections, each step is discussed and illustrated to explain how to build the framework.

4.1 Configuration of the Platform: Microsoft® Excel

The platform for implementing this research is based on the following architecture, Figure 28:

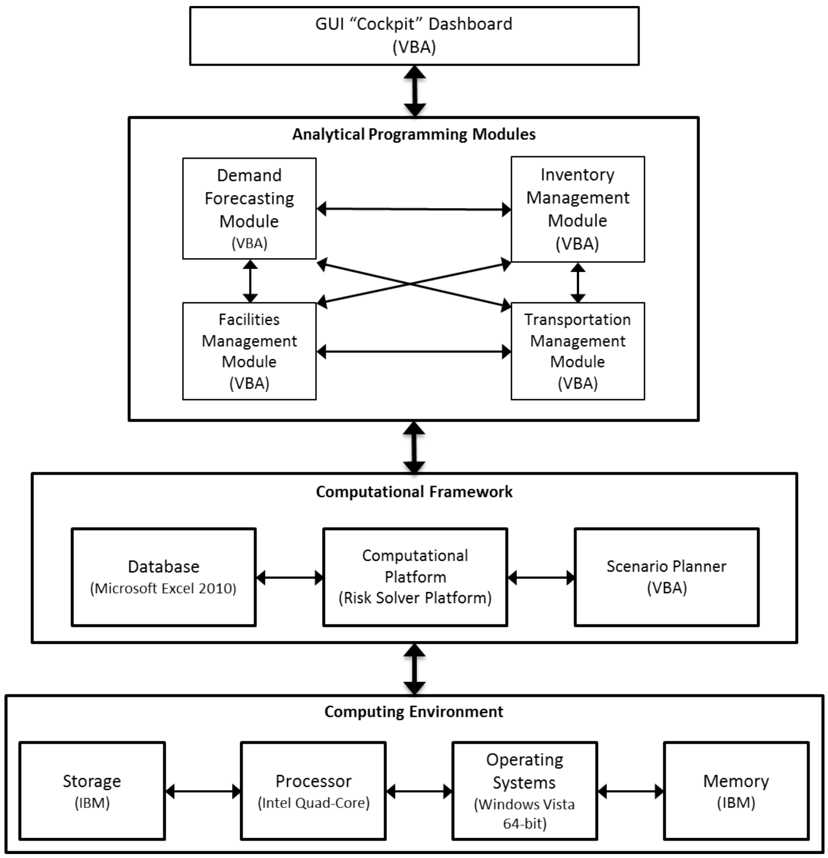


Figure 28: Simulation technology platform.

We installed and configured the latest version (v11.5) of Risk Solver Platform by Frontline Systems Inc into the latest version of Microsoft® Excel. Once installed, the Risk Solver Platform operates as an add-in within Microsoft® Excel.

4.2 Scenario Planning

The *integrated framework* follows the following five step process:

Step 1: Set up the nominal deterministic model.

Step 2: Perform scenario planning to identify the set of n possible future scenarios ($s_i = 1, 2, \ldots, n$).

Scenario Planning Step 1: Stakeholder's must identify seven (7) key uncertainties that describe the breadth of unknowns encompassing the supply chain network.

Uncertainty	**Description**
U1	Does off-shore manufacturing provide high-quality products?
U2	Are suppliers able to meet demand?
U3	Will consumers remain sensitive to price for IT components?
U4	Will demand trends reverse direction in the forecasted years?
U5	Can manufacturers outgoing capacity meet demand?
U6	Will consumer demand vary by region?
U7	Will customer's maintain a need (demand) for timely delivery?

Table 8: Seven uncertainties in the production of high-tech IT components.

In Table 8 are shown seven uncertainties that pertain to the general production of high-tech IT components and specifically to computer hard drives as they pertain to a firm that is producing high-tech components off-shore and importing to different countries.

Scenario Planning Step 2: Build a correlation matrix, Table 9, to establish the positive, +, and negative, -, relationship between the uncertainties.

	U1	U2	U3	U4	U5	U6	U7
U1		-	-	-	+	+	-
U2			-	+	+	+	-
U3				+	+	+	+
U4					+	+	-
U5						+	+
U6							-
U7							

$U_{ij} = U_{ji}$

Table 9: Correlation matrix of the seven key uncertainties.

In this step, the goal is to consolidate the "+" and "-"of the correlation matrix into three scenarios, distinguished in the following process:

(a) **Nominal Scenario**: Group the vertical columns that contain all the "+" relationships. The joint relationship of the U5 and U6 columns creates the nominal scenario: Suppliers are able to meet all demand and meet all the key uncertainties with price sensitive costs and reasonable capacity to meet expected demand.

(b) **Scenario 1** and **Scenario 2**: Group the horizontal rows that contain only the "+" relationship from both the vertical columns into two groups, creating a high and low:

Scenario 1: High-quality products with low sensitivity to price and unlimited manufacturer output capacity to meet all the variation in regional demand creates a high cost and high capacity scenario.

Scenario 2: High-quality products with high sensitivity to price and limited manufacturer output capacity to meet all the variation in regional demand creates a low cost and low capacity scenario.

	U1	U2	U3	U4	U5	U6	U7
U1		-	-	-	+	+	-
U2			-	+	+	+	-
U3				+	+	+	+
U4					+	+	-
U5						+	+
U6							-
U7							

$U_{ij} = U_{ji}$

Table 10: Correlation matrix with the key "+" uncertainties selected.

(c) The scenarios are then named and given descriptions, as summarized in Table 11:

Scenario#	**Scenario Name**	**Description**
Scenario 1, s_1	"High"	The "High" scenario utilizes high product and facility costs, for one product, with high capacity manufacturing facilities.
Scenario 2, s_2	"Nominal"	The "Nominal" scenario utilizes the average expected product and facility fixed costs, for one product.
Scenario 3, s_3	"Low"	The "Low" scenario utilizes low product and facilities cost, for one product, with low capacity manufacturing facilities.

Table 11: Scenario planning implementation summary.

(d) Take a decision-analytic approach to determine the probability, p_i, of each possible future scenario, s_i. Shown in Table 12 are the probabilities utilized in our work.

	Scenario 1 s_1 **HIGH**	**Scenario 2** s_2 **NOMINAL**	**Scenario 3** s_3 **LOW**
Base Case	$p_1 = 33\%$	$p_2 = 33\%$	$p_3 = 33\%$
Case 1	$p_1 = 100\%$	0	0
Case 2	0	$p_2 = 100\%$	0
Case 3	0	0	$p_3 = 100\%$

Table 12: Scenario planning configuration parameters.

(e) Compute the most likely future scenario, $\boldsymbol{S} = \sum_{i=1}^{n} p_i s_i$.

Notation:		
i	$\triangleq$	index value for scenarios
n	$\triangleq$	number of total scenarios
s_i	$\triangleq$	scenario s_i for $i = 1, \ldots, n$
p_i	$\triangleq$	scenario probability(%) of occurence for $i = 1, \ldots, n$
$\boldsymbol{S}$	$\triangleq$	probability weighted sum of best future scenario

Table 13: Table of notation scenario-planning.

(f) Model the supply chain network and compute a solution which minimizes the total cost objective function, for the most probable future scenario, $\boldsymbol{S}$.

(g) Perform a probability parametric analysis of the coefficient of variation of demand, using a normal distributions function with $\pm 3\sigma$ to define demand and study the effect on the coefficient of variation of supply and the total cost of the supply chain network design.

4.3 Demand Forecasting Analysis

Determine the optimal forecasted demand using the following process:

Step 1: Reference the formulations, Excel worksheet and Excel charts from Section 3.1

Step 2: Build the complete inter-linked Excel workbook framework for demand forecasting with the static and adaptive methods.

Step 3: Input data for the demand history

Step 4: Adjust the adaptive forecasting coefficients

(a) Exponential: α

(b) Holt's: α, β

(c) Winter's: α, β, and γ

Step 5: Determine the optimal forecasted annual demand as shown in Figure 29.

SUMMARY RESULTS clear

Compare All Model | MAPE Analysis | View Best Model

Best Model	Static Forcast
Year 6 Demand (units)	31579
Year 7 Demand (units)	35354
Average Annual Forecast	33467

Figure 29: Summary results of the demand forecasting best model.

After computing the $(MAPE)_t$ for each forecasting method, determine the optimal forecasting method by selecting the forecasting method that yields the lowest $(MAPE)_t$ at the current time, t. The optimal forecast method is the one with the smallest $(MAPE)_t$. Once the best forecasting method has been established, determine the optimal forecasted demand, using the corresponding optimal forecasting method that produced the lowest $(MAPE)_t$.

Notation:		
i	$\triangleq$	generic index identifier for a forecast method
$i = 1$	$\triangleq$	index value for the static method
$i = 2$	$\triangleq$	index value for the moving average method
$i = 3$	$\triangleq$	index value for the exponential method
$i = 4$	$\triangleq$	index value for the Holt's method
$i = 5$	$\triangleq$	index value for the Winter's method
t	$\triangleq$	present time period
$\mathcal{B}$	$\triangleq$	minimum $(MAPE)_t^i$ at time t, for a forecast method i
$\mathcal{F}_i$	$\triangleq$	reasonalized forecast quantity: for the corresponding method, $i = 1, 2, 3, 4, 5$
$\mathcal{F}_2$	$\triangleq$	reasonalized forecast quantity: moving average
$\mathcal{F}_3$	$\triangleq$	reasonalized forecast quantity: Exponential method
$\mathcal{F}_4$	$\triangleq$	reasonalized forecast quantity: Holt's method
$\mathcal{F}_5$	$\triangleq$	reasonalized forecast quantity: Winter's method
$\mathfrak{D}$	$\triangleq$	total quantity of the reasonalized forecast

Table 14: Table of notation for determining the optimal forecasting method

Step 1: Compute the static forecast and error analysis. Tabulate all the results.

Step 2: Compute the moving average forecast and error analysis. Tabulate all the results.

Step 3: Compute the exponential forecast and error analysis. Tabulate all the results.

Step 4: Compute the Holt's forecast and error analysis. Tabulate all the results.

Step 5: Compute the Winter's forecast and error analysis. Tabulate all the results.

Step 6: Tabulate the results of the forecasting $(MAPE)_t$, for each forecasting method as shown in Table 15.

Forecast Method	$(MAPE)_t^i$
Static:	$(MAPE)_t^1$
Moving Average:	$(MAPE)_t^2$
Exponential:	$(MAPE)_t^3$
Holt's:	$(MAPE)_t^4$
Winter's:	$(MAPE)_t^5$

Table 15: An example of the tabulation for a comparative analysis of the $MAPE$.

Step 7: Determine the optimal forecasting model, $\mathcal{B}$, corresponding to the minimum $(MAPE)_t^i$, $i = 1, 2, 3, 4, 5$ at present time t.

$$\mathcal{B} \triangleq \text{Min } (MAPE)_t^i \tag{4.1}$$

Step 8: Determine the total forecasted demand quantity, $\mathfrak{D}$, for all future periods ($t = 1, 2, 3, \dots$) and ($\ell = 1, 2, 3, \dots$), utilizing the optimal forecasting method that is corresponding to the $\mathcal{B}$. The automation process for determining the optimal forecast, and the corresponding optimal forecasted demand quantity is:

if $\mathcal{B} = (MAPE)_t^1$ **then**

$$\mathfrak{D} = \sum_{j=t}^{t+\ell} (F_1)_j$$

else if $\mathcal{B} = (MAPE)_t^2$ **then**

$$\mathfrak{D} = \sum_{j=t}^{t+\ell} (F_2)_j$$

else if $\mathcal{B} = (MAPE)_t^3$ **then**

$$\mathfrak{D} = \sum_{j=t}^{t+\ell} (F_3)_j$$

else if $\mathcal{B} = (MAPE)_t^4$ **then**

$$\mathfrak{D} = \sum_{j=t}^{t+\ell} (F_4)_j$$

else if $\mathcal{B} = (MAPE)_t^5$ **then**

$$\mathfrak{D} = \sum_{j=t}^{t+\ell} (F_5)_j$$

end if

The value for $\mathfrak{D}$ represents the optimal total of the forecasted demand quantity, for ℓ periods. As stated in the preceding Motivation, Section 1.1 of our work, the concern of a global supply chain is to view the annualized basis. Therefore the $\mathfrak{D}$ value needs to be converted to an average annualized forecast demand, $\overline{\mathfrak{D}}$. For example, if there are three years of annual forecasted demand, it is appropriate to divide the sum of the three years by three, in order to attain an average annual demand.

It is the quantity value of $\overline{\mathfrak{D}}$ that is utilized as the average annual demand for all further analysis in the supply chain. Therefore, the numeric value of $\overline{\mathfrak{D}}$ is used in the subsequent sections when the annual forecasted demand quantity is required.

4.4 Inventory Management Analysis

This part of the research work is only concerned with illustrating how to build and program in VBA and Excel an *Inventory Management Module*, a software-based type calculator, as part of the GUI, because it is an important part of studying supply chains. This research work is not specifically addressing or studying inventory analysis as part of the simulation or numerical case study analysis. As part of this thesis research, the following section is provided, for instructional purposes, on how to program an inventory management calculator in Excel with VBA.

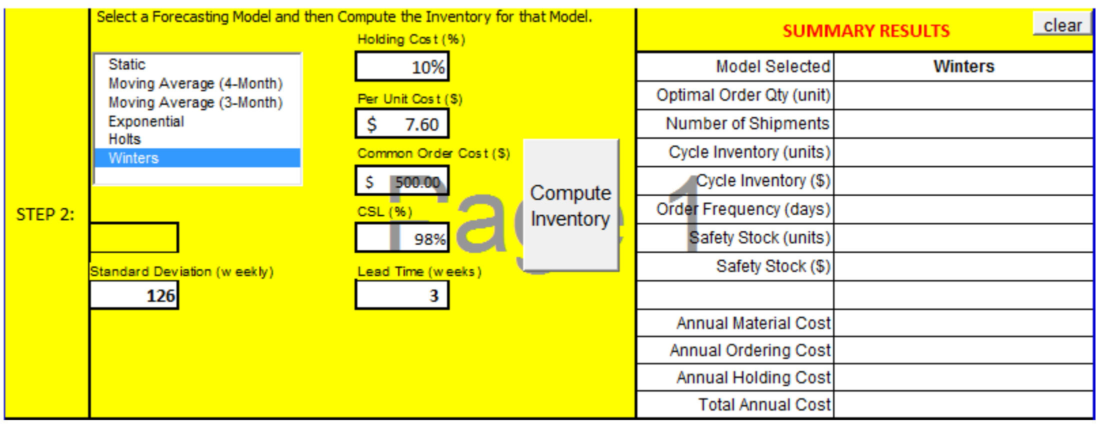


Figure 30: Inventory management module.

To perform the inventory analysis computations, the *inventory analysis module* is utilized:

1. Reference the formulations from Section: 4.4.
2. Build the Excel workbook framework for the inventory analysis module as show in Figure 30
3. Adjust the inventory input parameter values using the inventory module.
4. Determine the optimal inventory values using the *Compute Inventory* button.

As presented in Figure 30, *Step 2: Compute Inventory*, the user is able to select the forecasting method and adjust the input values of the inventory management. Upon the button click of the *Compute Inventory* button, the computations are performed by the VBA code in *Appendix: VBA Code for the Modules in Section 7* and the results are presented in the *Step 2: Summary Results*.

4.5 Facilities Management

4.5.1 The Two-stage Capacitated Plant Deterministic Model

Developing the two-stage capacitated plant deterministic model followed these steps:

(1) Reference the equations from the model formulation from Section 3.3.2.

(2) Build the Excel worksheet architecture for a two-stage capacitated plant problem to include the scenario planning results. The generalized frameworks are discussed within Chopra and Meindl (2010).

4.5.2 Expanding to the Multi-Echelon Capacitated Plant

To process for expanding the framework to a multi-echelon capacitated plant problem with $n = 3$ scenarios, was:

(1) Reference the equations from the model formulation from Equation (3.63) in Section 3.3.3.

(2) Update the problem formulation to consider scenarios.

The problem formulation from Equation (3.63) is reformulated and expanded to consider the $n = 3$ scenarios. The scenario notation for i is enclosed in a bracket, identified by $[i]$. Since there are $[n] = 3$ scenarios, we consider the capacity, product cost and fixed infrastructure cost of each manufacturer scenario and update the problem formulation as follows:

$$\text{Minimize } \sum_{f=1}^{j} F_{s_f} y_f + \sum_{f=1}^{j}\sum_{g=1}^{k} c1_{fg} q1_{fg} + \tag{4.2}$$

$$\underbrace{\sum_{i=1}^{n} p_i \left[\sum_{g=1}^{k} F_{m_g}^{[i]} y_g^{[i]} + \sum_{g=1}^{k}\sum_{h=1}^{m} c2_{gh}^{[i]} q2_{gh}^{[i]} \right]}_{\text{manufacturer with scenarios}} + \tag{4.3}$$

$$\sum_{h=1}^{m}\sum_{i=1}^{n} c3_{hi} q3_{hi} + \sum_{h=1}^{m} F_{d_h} y_h + \sum_{i=1}^{n} F_{r_i} y_i, \tag{4.4}$$

subject to (4.5)

$$S_f y_f - \sum_{g=1}^{k} q1_{fg} \geq 0 \text{ for } f = 1, \ldots, j, \tag{4.6}$$

$$\sum_{f=1}^{j} q1_{fg} - \sum_{h=1}^{m} q2_{gh}^{[i]} \geq 0 \text{ for } g = 1, \ldots, k, [i] = 1, \ldots, [n], \tag{4.7}$$

$$M_g^{[i]} y_g^{[i]} - \sum_{h=1}^{m} q2_{gh}^{[i]} \geq 0 \text{ for } g = 1, \ldots, k, [i] = 1, \ldots, [n], \tag{4.8}$$

$$\sum_{g=1}^{k} q2_{gh}^{[i]} - \sum_{i=1}^{n} q3_{hi} \geq 0 \text{ for } h = 1, \ldots, m, [i] = 1, \ldots, [n], \tag{4.9}$$

$$D_h y_h - \sum_{i=1}^{n} q3_{hi} \geq 0 \text{ for } h = 1, \ldots, m, \tag{4.10}$$

$$\sum_{i=1}^{n} \mathfrak{D}_i - \sum_{h=1}^{m} q3_{hi} = 0 \text{ for } i = 1, \ldots, n, \tag{4.11}$$

and

$$y_f, y_g, y_h, y_i \in \{0, 1\}, q1_{fg}, q2_{gh}^{[i]}, q3_{hi} \geq 0. \tag{4.12}$$

(3) Build the Excel worksheet architecture for the multi-echelon capacitated problem. The frameworks are provided in detail in the following subsection: Configuring the Excel Worksheet Architecture.

(4) Automate the process using Solver and VBA programming language and integrate into a GUI dashboard as provided in *Appendix: VBA Code for the Modules in Section 7.*

4.5.3 Configuring the Excel Worksheet Architecture

With the updated problem formulation to consider $n = 3$ scenarios, the generalized excel worksheet architecture is formatted as follows:

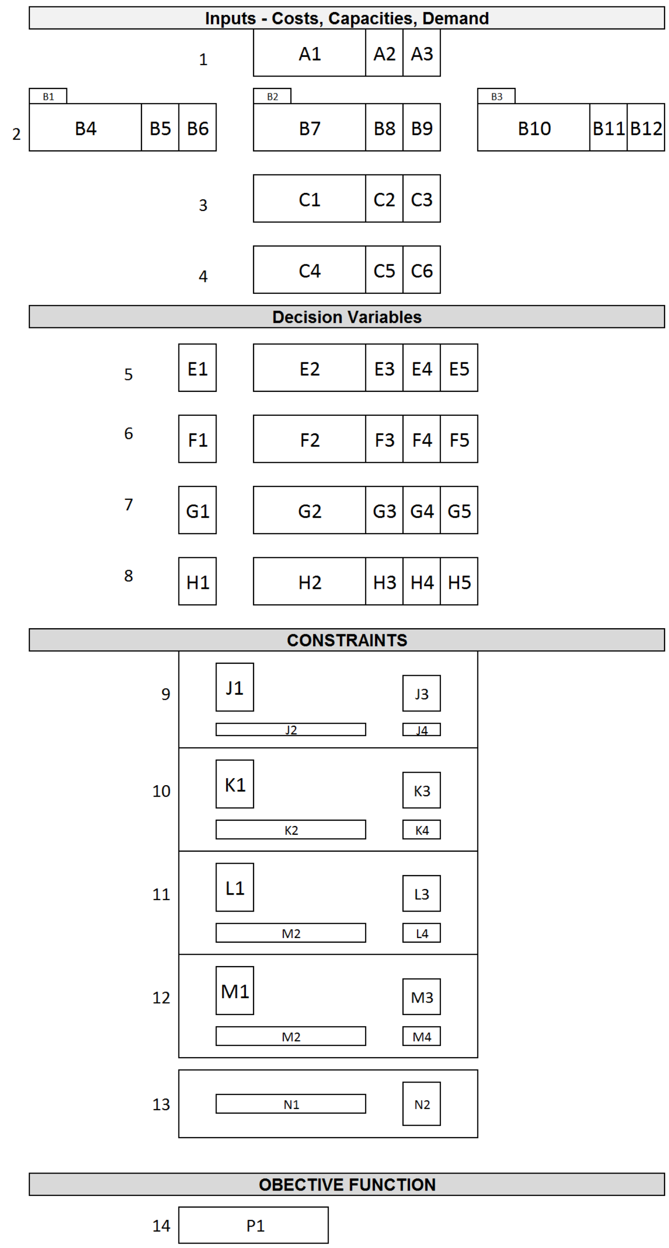


Figure 31: Generalized Excel worksheet framework for multi-echelon supply chain network.

The worksheet architecture to enter cost inputs with $n = 3$ scenarios is formatted as:

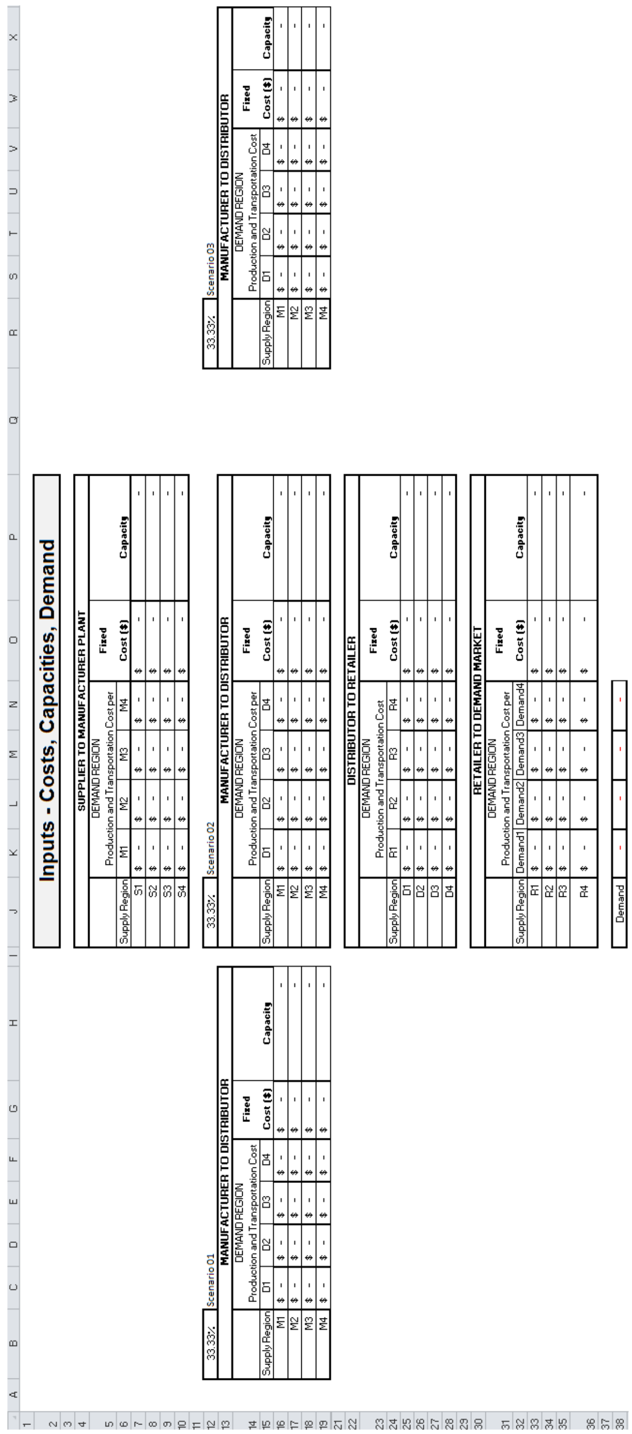


Figure 32: Excel worksheet structure of inputs (costs, capacities, and demand)

The decision variables in the worksheet architecture is formatted as follows:

Decision Variables

Flow In to Supplier		Supply Region	M1	M2	M3	M4	(1, open) (0, closed) Yf	Max Supplier Capacity S_f	Flow Out From Supplier
			Demand Region - Product Allocation						
200000	-->	S1	0	0	0	0	0	-	0
200000	-->	S2	0	0	0	0	0	-	0
200000	-->	S3	0	0	0	0	0	-	0
200000	-->	S4	0	0	0	0	0	-	0
			0	0	0	0			0

Flow In to Man.		Supply Region	D1	D2	D3	D4	(1, open) (0, closed) Yq		Flow Out from Manufact.
			Demand Region - Product Allocation						
0	-->	M1	0	0	0	0	0	-	0
0	-->	M2	0	0	0	0	0	-	0
0	-->	M3	0	0	0	0	0	-	0
0	-->	M4	0	0	0	0	0	-	0
			0	0	0	0			0

Flow In Distributor		Supply Region	R1	R2	R3	R4	(1, open) (0, closed) Y_k	Distributor Capacity D_h	Flow out From Distributor
			Demand Region - Product Allocation						
0	-->	D1	0	0	0	0	0	-	0
0	-->	D2	0	0	0	0	0	-	0
0	-->	D3	0	0	0	0	0	-	0
0	-->	D4	0	0	0	0	0	-	0
			0	0	0	0			0

Flow In to Retailer		Supply Region	Demand 1	Demand 2	Demand 3	Demand 4	(1, open) (0, closed) Y_i	Retailer Capacity R_i	Flow out from Retailer
			Demand Region - Product Allocation						
0	-->	R1	0	0	0	0	0	-	0
0	-->	R2	0	0	0	0	0	-	0
0	-->	R3	0	0	0	0	0	-	0
0	-->	R4	0	0	0	0	0	-	0

Figure 33: Excel worksheet structure of decision variables.

The constraints portion in the worksheet architecture is formatted as follows:

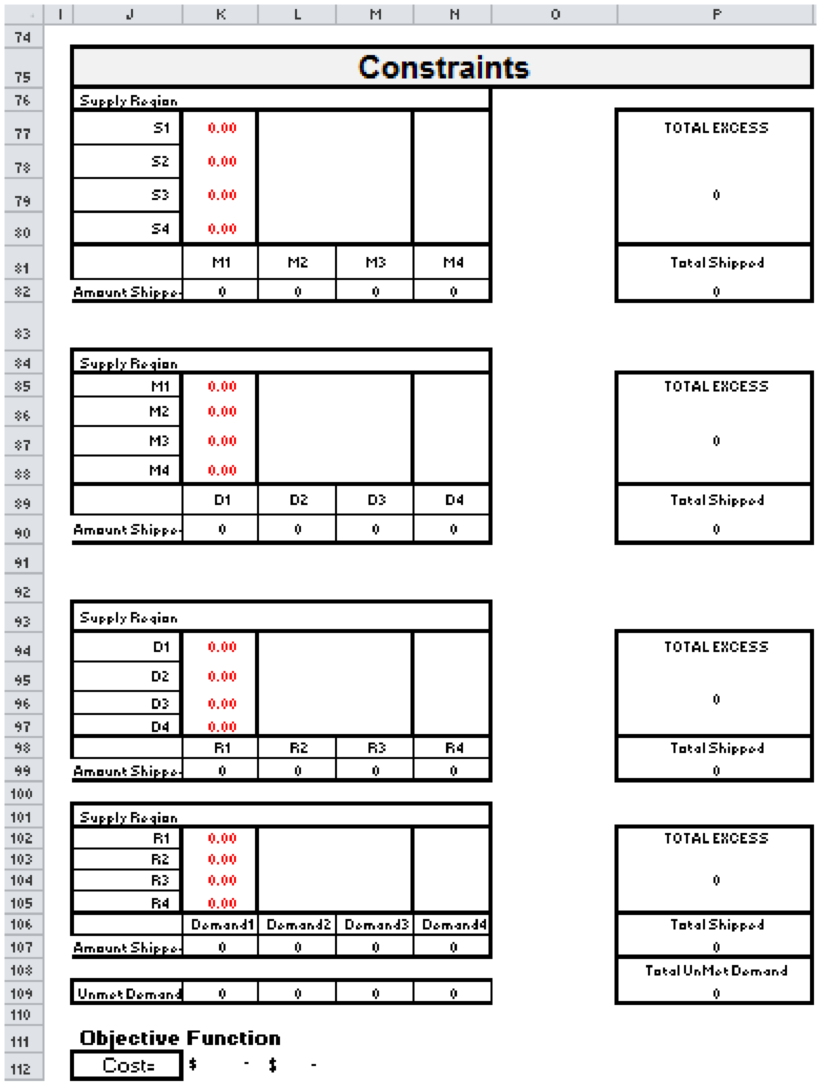


Figure 34: Excel worksheet structure of constraints.

The Excel programming reference, based on the Figure 31 generalized architecture is:

```
=SUMPRODUCT(E2_,A1_)+SUMPRODUCT(E3_,A2_)+B1_(SUMPRODUCT(F2_,
    B4_)+SUMPRODUCT(F3_,B5_))+B2_(SUMPRODUCT(F2_,B7_)+
    SUMPRODUCT(F3_,B8_))+B3_(SUMPRODUCT(F2_,B10_)+SUMPRODUCT(
    F2_,B11_))+SUMPRODUCT(G2_,_C1)+SUMPRODUCT(G3_,_C2)+
    SUMPRODUCT(H2_,D1_)+SUMPRODUCT(H3_,D2_)
```

The entire worksheet architecture, using $n = 3$ scenarios is then formatted as follows:

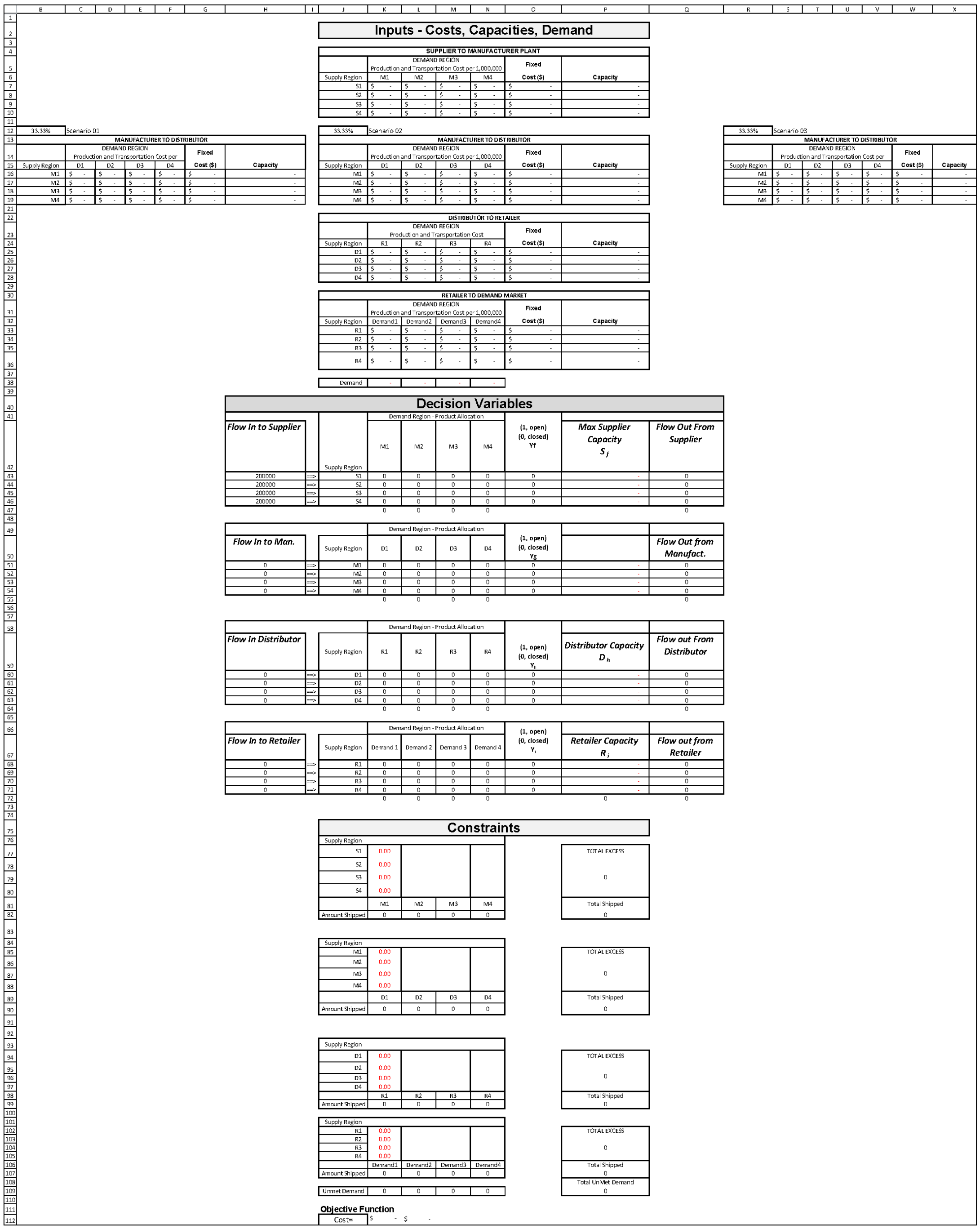


Figure 35: Excel worksheet structure of constraints.

The function for the objective function is defined by the following Excel formula:

```
=SUMPRODUCT(K43:N46,K7:N10)+SUMPRODUCT(O43:O46,O7:O10)+$B$12*(
    SUMPRODUCT(K51:N54,C16:F19)+SUMPRODUCT(O51:O54,G16:G19))+
    $J$12*(SUMPRODUCT(K16:N19,K51:N54)+SUMPRODUCT(O16:O19,O51:O54
    ))+$R$12*(SUMPRODUCT(S16:V19,K51:N54)+SUMPRODUCT(W16:W19,O51
    :O54))+SUMPRODUCT(K60:N63,K25:N28)+SUMPRODUCT(O60:O63,O25:O28
    )+SUMPRODUCT(K68:N71,K33:N36)+SUMPRODUCT(O68:O71,O33:O36)+
    PsiOutput()
```

4.5.4 Demand Uncertainty with Monte Carlo Simulation

To implement a Monte Carlo simulation in Excel, the Risk Solver Platform add-in is required. The following subsections describe the methods used to perform the analysis.

4.5.5 Configuring the Simulation Uncertainty Functions

The normal distribution function for demand requires two parameters:

(1) The mean, μ

(2) The standard deviation, σ.

The average annual demand quantity is needed, $\mu = \overline{\mathfrak{D}}$. This value of μ serves as the equivalent of the mean annual demand parameter, for each region, in the normally distributed uncertainty functions within the Risk Solver Platform programming configuration for the demand generation functions in the simulation. Therefore, it is essential that $\mathfrak{D}$ is converted to an annual basis value, to remain consistent throughout the analysis.

The normal distributions functions are developed using three Risk Solver Platform *Psi* functions, which are nested together, in the following process:

(1) **PsiSimNormal**: The normal distribution is defined by the $PsiSimNormal(\mu,\sigma)$ function, in which the input parameters are the $\mu \triangleq Mean$ and $\sigma \triangleq$ standard deviation. To model uncertainty, our work utilizes σ as a "multiplicative" of μ (Junga et al., 2004) such that $\sigma = \mu * CV$. In the Monte Carlo simulation, the (CV) is set to incrementally increase from .01% to .50%, thereby widening the range of σ, over ten simulations. Figure 36 shows an example of an output from the $PsiSimNormal(\mu, \sigma)$, function with $\mu = 10, (CV)_D = 10\%$ and $\sigma = \mu * (CV)_D$. It is clear that this approach of using σ as a "multiplicative" of μ produces the desired result and is a suitable approach to adjusting the $(CV)_D$.

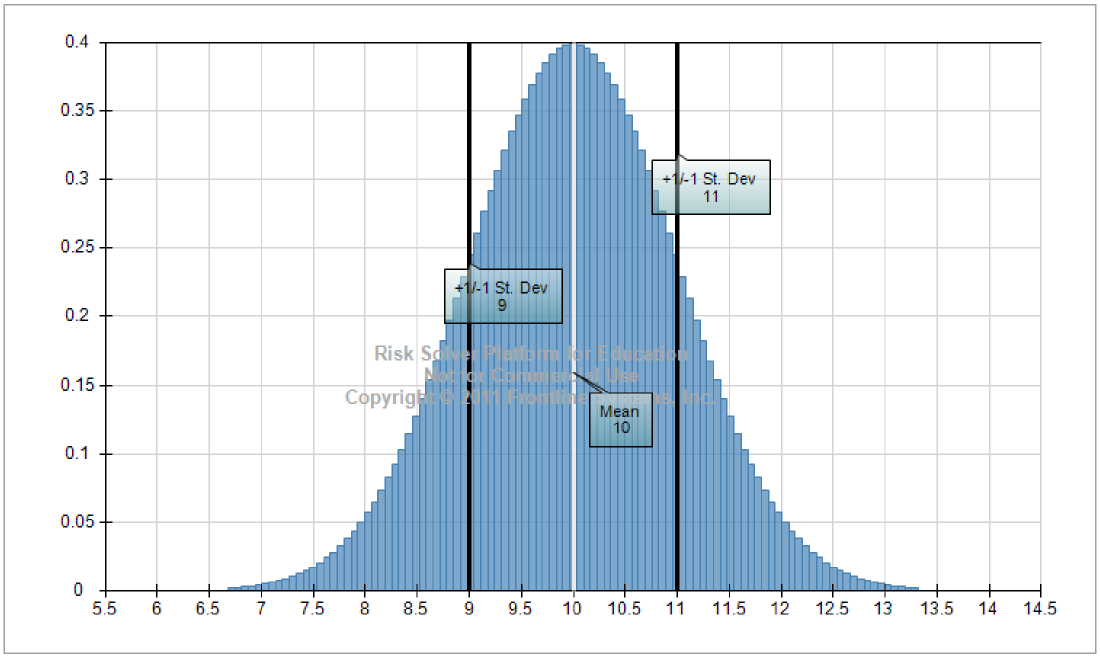


Figure 36: Example of *PsiNormal( )* function for a normal distribution function.

(2) **PsiSimParam**: The adjustment of the $(CV)_D$ in the simulations is performed automatically by the Risk Solver Platform $PsiSimParam$ function, defined by $PsiSimParam(lower, upper)$, with: $lower \triangleq the\ lower\ value\ of\ a\ range$; $upper \triangleq the\ upper\ value\ of\ a\ range$. The range used in our work is .01% to 50%.

(3) **PsiTruncate**: Lastly, is the truncating function, $PsiTruncate(lower, upper)$, in which $lower \triangleq lower\ value\ of\ a\ range$ and $upper \triangleq upper\ value\ of\ a\ range$. The $PsiTruncate()$ function is useful when nested within the $PsiSimParam()$ because as the (CV) values increase (which are used to define the σ range increase from a lower (e.g., .01%) to upper (e.g., 50%) range over the ten simulations) the $PsiTruncate()$ function ensures the demand value output from the $PsiSimNormal()$ function is automatically adjusted, with each simulation, so that demand is constrained within a defined range for the desired standard deviation. In our work, the analysis was constrained to the $Max(0, -3\sigma)$ on the left side of the mean to ensure demand is never negative (Chopra and Meindl, 2010,

pg. 358). The range automatically adjusts with each incremental parameter of the simulation in which demand is never negative on the lower range and $(+3\sigma)$ on the right side of the mean. This research goes on to use $\pm 3\sigma$. This method of using the $PsiTruncate()$ ensures that for all values in the analysis the demand quantity is nonnegative. If further research calls for six sigma analysis with normal distribution, then the use of the $PsiTruncate()$ can be widened. The generalized Excel formula is:

$$\begin{aligned}
=&PsiNormal(\mu, \mu * PsiSimParam(.01\%, 50\%),\\
&PsiTruncate((Max(0, \mu - 3(\mu * PsiSimParam(.01\%, 50\%))),\\
&(\mu + 3(\mu * PsiSimParam(.01\%, 50\%)))).
\end{aligned} \tag{4.13}$$

After performing the Monte Carlo Simulation, the results are tabulated for subsequent analysis of the numerical results.

4.5.6 Configuring the Simulation Parameters

The Monte Carlo random number generator is based on CMRG. The simulation optimization parameters are shown in Figure 37.

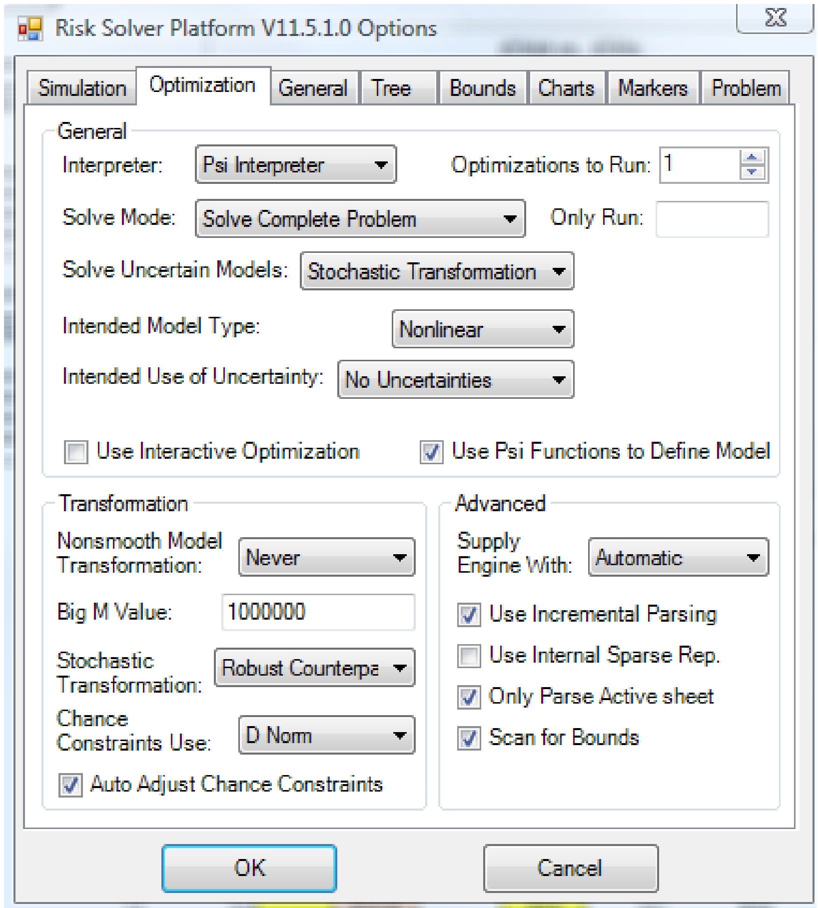


Figure 37: Risk Solver Platform configurations.

Set Target Cell: \$D\$112

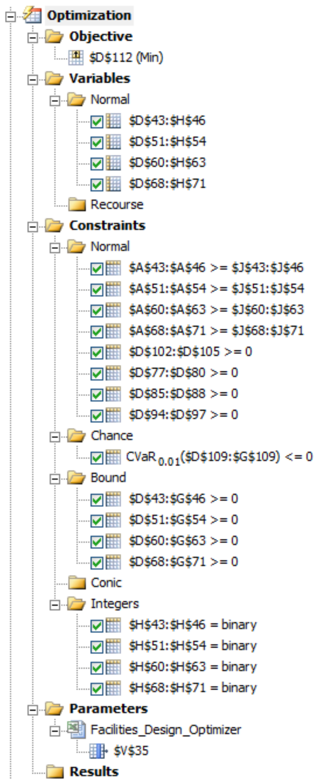
Equal To: Min

By Changing Cells: \$D\$43:\$H\$46,\$\$51:\$H\$54,\$D\$60:\$H\$63,\$D\$68:\$H\$71

Subject to the constraints:

Figure 38: Risk Solver Platform parameters.

(a) Software configuration



(b) Programming configuration

$\$A\$43 : \$A\$46$	$\geq$	$\$J\$46$
$\$A\$54 : \$A\$54$	$\geq$	$\$J\$54$
$\$A\$63 : \$A\$63$	$\geq$	$\$J\$63$
$\$A\$71 : \$A\$71$	$\geq$	$\$J\$71$
$\$G\$107 : \$I\$107$	$=$	$\$H\$38$
$\$D\$102 : \$D\$105$	$\leq$	$= 0$
$CVaR_{.01}(\$D\$109 : \$G\$109)$	$\geq$	$= 0$
$\$D\$43 : \$G\$46$	$\geq$	$= 0$
$\$D\$51 : \$G\$54$	$\geq$	$= 0$
$\$D\$60 : \$G\$63$	$\geq$	$= 0$
$\$D\$68 : \$G\$71$	$\geq$	$= 0$
$\$D\$77 : \$D\$80$	$\geq$	$= 0$
$\$D\$85 : \$D\$88$	$\geq$	$= 0$
$\$D\$94 : \$D\$97$	$\geq$	$= 0$
$\$H\$38$	$=$	$\$J\$72$
$\$H\$43 : \$H\$46$	bin	$= binary$
$\$H\$51 : \$H\$46$	bin	$= binary$
$\$H\$60 : \$H\$46$	bin	$= binary$
$\$H\$68 : \$H\$46$	bin	$= binary$
$\$I\$107 : \$H\$46$	$=$	$\$H\$38$
$\$I\$43 : \$I\$46$	$\geq$	$\$J\$43 : \$J\$46$
$\$I\$51 : \$I\$46$	$\geq$	$\$J\$51 : \$J\$54$
$\$I\$60 : \$I\$46$	$\geq$	$\$J\$60 : \$J\$63$
$\$I\$68 : \$I\$46$	$\geq$	$\$J\$68 : \$J\$71$
$\$I\$78$	$=$	$= 0$
$\$I\$86$	$=$	$= 0$
$\$I\$95$	$=$	$= 0$

The implementation of ten simulations and ten thousand trials per simulation are used to cover the $PsiSimParm(.01\%, 50\%)$ range. This range for the $PsiSimParam()$ is utilized as the multiple of the average of demand,μ, to create the increasing parameters for the standard deviation within the format required for the $PsiNormal(\mu, \sigma)$.

In our work, the use of chance constraints was utilized to facilitate the Monte Carlo simulation and because we are also solving for the binary decision variables for the facilities being opened/closed. To explain a chance constraint we source Frontline Systems, Inc. (2011)(version 11.5.1.0): "If a constraint depends on uncertain parameters and normal decision variables, we must specify what it means for the constraint to be satisfied. There are many possible realizations for the uncertain parameters, but only single values for the decision variables. The Solver must find values for the decision variables that cause the constraint to be satisfied for all, or perhaps most but not all, realizations of the uncertainties. We call this a chance constraint." In our work, a chance constraint was configured to a strict value of 1%. This chance constraint parameter for the simulation was set to such a strict value to ensure that the unmet demand quantity must be less than or equal to zero, with only a 1%. Restated, the 1% chance constraint setting was used to ensure that the supply quantity meet at the least 99% of the demand quantity.

4.5.7 Supply Chain Network Design Configuration Mapping

Th software module that was developed for the mapping of the supply chain network utilizes the results of the open/close binary values to determine if a facility is opened or closed. The quantity values associated from the decision variables determine if a connection is needed between the nodes. The network diagram updates each time the simulation concludes. An example of the network mapping output is shown in Figure 39. The automated networking mapping module is entirely programmed using VBA code, provided in the *Appendix: VBA Code for the Modules in Section 7*.

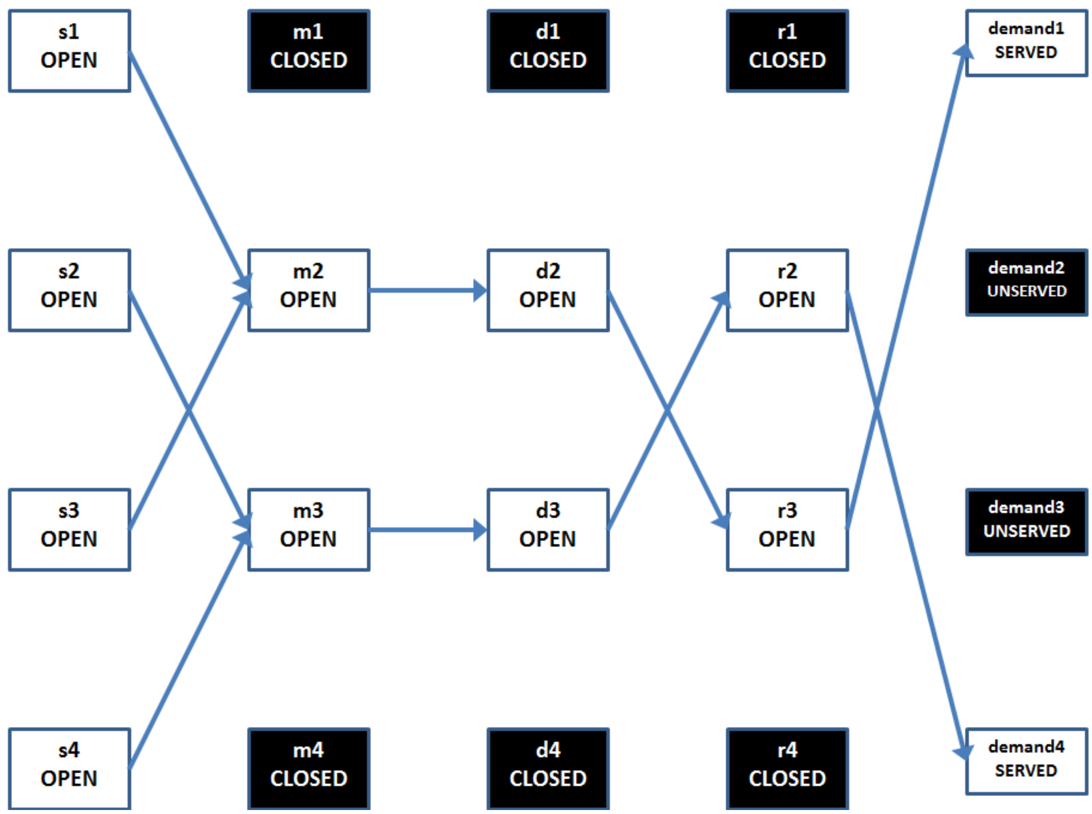


Figure 39: Example of the supply chain network design configuration mapping.

4.6 Dashboard/Cockpit Automation

In our work, the best forecasting model for the demand is performed using: *DetermineOptimalModel( )* VBA code module. The inventory management was automated using: *ComputeInventory( )* VBA code module. The Solver language automated for the facilities design in the *ComputeFacilitiesDesign( )* VBA code module and the Monte Carlo Simulation is automated using the *ComputeSimulation( )* VBA code module.

The primary purpose of the software automation system developed as part of this research is to automate the computations for analyzing a supply chain network design. This work presents the automation code developed using VBA programming code within Excel to harness the spreadsheet power of Excel along with practical and rapid prototyping tools of the VBA and Solver languages. The software code was developed in modules and various macros and functions were written to perform the computations. Functions are assigned to GUI buttons (Bovey et al., 2009) to allow for easy button click operation of the programming code.

Each of these VBA functions call other important subfunctions. These high level functions provide the starting point for understanding the mechanisms of the code for the software developed in our work. The entire programming language code of declarations is documented in the *Appendix: VBA Code for the Modules in Section 7*. In the dashboard architecture, user can update the α, β, and γ parameters for the demand forecasting and change the forecasting method. An initial concept of the dashboard cockpit design is presented in Figure 40. The dashboard is designed to quickly present numerical and graphical results including:

1. Overall total profitability summary results and graphs;
2. Demand summary results and graphs;
3. Inventory summary results and graphs;
4. Facility design summary results and graphs; and

5. Transportation design summary results and graphs.

The dashboard display was designed to be easy to interpret and update quickly upon changes to input parameters. Scenarios are saved to a database for easy retrieval and saving of work for a later date. Decision recommendations can be presented based on the results. Each module is integrated to share data with the other modules. Additionally, each module pushes the data into the dashboard. The data is presented in an adaptive format so that a change in the input parameter automatically permeates throughout the supply chain network design and updates the dashboard results.

When using automated software application tools, it is important to be able to quickly and effectively make changes to the input parameters that quickly update the output results. This software feature enables quick decision-making and improves productivity. The design of an airplane cockpit has been adopted into the software development arena as a method of design to accomplish this goal of efficiently updating parameters to quickly gain results of updated information delivery.

In the automation software developed in our work, the concept of a cockpit and dashboard control panel are developed and utilized to facilitate the updating of the parameters for the adaptive forecasting parameters. In the demand entry form worksheet, Figure 40, the demand data is entered and the parameters for the forecasting techniques can be easily adjusted using a *spin button* configured between 0 and 1.

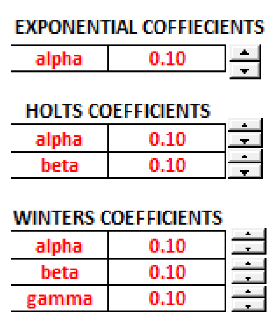


Figure 40: Cockpit controls for demand entry parameters.

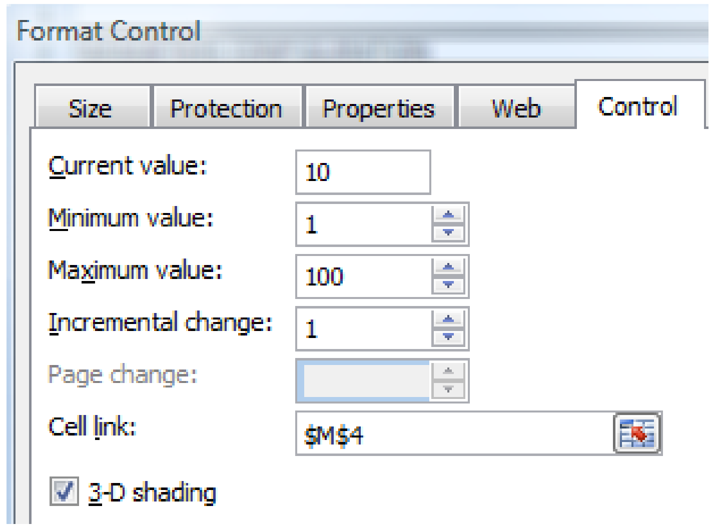


Figure 41: Format control for spin buttons.

An issue of using Excel (version 2010 Professional) and adjusting the adaptive forecasting coefficients with *spin control buttons* is that the controls can only process values greater than 1. However, the coefficients values are less than 1. Therefore the spin controls buttons cannot directly be used for the dashboard GUI. A solution is to set the target cell for the coefficients to be a value greater than one, and then in an adjacent cell, divide this target cell by 100. It is this value in the adjacent cell that is displayed in the GUI. The target cell is hidden (e.g., same color font as the background) and the adjustments that are made to the spin buttons immediately update the coefficients for the forecasting and the charts in the dashboard are updated in real-time.

5 Simulation Study and Numerical Analysis

Our work creates a two-step process to the simulation and numerical analysis for quantifying the effects of demand uncertainty on a supply chain network and the corresponding outputs of measuring supply and total cost. Only the *Demand Forecasting* and *Facilities Management Modules* are utilized in the simulation study.

First, we present a set of calibration problems, each with known inputs and known expected outputs that are used to validate that the implementation of the framework has been constructed correctly. Second, we present the analysis of a Base Case, Case 1, 2, and 3 each with $n = 3$ scenarios for product cost, fixed facilities costs, and facility capacity. The analysis of the case studies measures the effect of varying the coefficient of variation of demand on the coefficient of variation of supply in the SCN and the relationship to total cost.

The implementation of the software is discussed in Section 4. The environment is a Windows Vista platform running a 64-bit OS and Microsoft® Excel 2010 Professional with the Front Line Systems Inc. Risk Solver Platform version 11.5 add-in.

5.1 Calibration 01

Step 1: Problem Input values

A manufacturer has four sites (m_1, m_2, m_3, m_4), each with fixed infrastructure cost of \$1,000 and capacity of 10,000 units. The manufacturer has four separate suppliers (s_1, s_2, s_3, s_4), four distributors (d_1, d_2, d_3, d_4) and four retailers (r_1, r_2, r_3, r_4). The transportation costs between all the facilities shares the following structure cost/unit(\$).

	Facility 1	Facility 2	Facility 3	Facility4
Facility 1	\$1	\$2	\$3	\$4
Facility 2	\$2	\$1	\$2	\$3
Facility 3	\$3	\$2	\$1	\$2
Facility 4	\$4	\$3	\$2	\$1

Table 16: Transportation costs between all the facilities.

The maximum capacity (quantity of units output) for each facility type is:

Facility Type	Capacity(units)
Supplier	10,000
Manufacturer	10,000
Distributor	10,000
Retailer	10,000

Table 17: Maximum capacity for each facility type.

The average annual demand at four market end points has been forecasted for total of: 40,000 *units/year*. Shown in Figure 42 are "Input of cost, capacities and demand for calibration problem 1", in which regions $\overline{\mathfrak{D}}_2$ and $\overline{\mathfrak{D}}_3$ equally have 20,000 *units/year* and regions $\overline{\mathfrak{D}}_1$ and $\overline{\mathfrak{D}}_4$ are zero.

Inputs - Costs, Capcaities, Demand						
SUPPLIER TO MANUFACTURER PLANT						
	DEMAND REGION Production and Transportation Cost per 1,000,000				**Fixed**	
Supply Region	M1	M2	M3	M4	**Cost ($)**	**Capacity**
S1	$ 1	$ 2	$ 3	$ 4	$ 1,000	10,000
S2	$ 2	$ 1	$ 2	$ 3	$ 1,000	10,000
S3	$ 3	$ 2	$ 1	$ 2	$ 1,000	10,000
S4	$ 4	$ 3	$ 2	$ 1	$ 1,000	10,000
MANUFACTURER TO DISTRIBUTOR						
	DEMAND REGION Production and Transportation Cost per 1,000,000				**Fixed**	
Supply Region	D1	D2	D3	D4	**Cost ($)**	**Capacity**
M1	$ 1.00	$ 2.00	$ 3.00	$ 4.00	$ 1,000.00	20,000.00
M2	$ 2.00	$ 1.00	$ 2.00	$ 3.00	$ 1,000.00	-
M3	$ 3.00	$ 2.00	$ 1.00	$ 2.00	$ 1,000.00	-
M4	$ 4.00	$ 3.00	$ 2.00	$ 1.00	$ 1,000.00	20,000.00
DISTRIBUTOR TO RETAILER						
	DEMAND REGION Production and Transportation Cost per 1,000,000				**Fixed**	
Supply Region	R1	R2	R3	R4	**Cost ($)**	**Capacity**
D1	$ 1.00	$ 2.00	$ 3.00	$ 4.00	$ 1,000.00	20,000.00
D2	$ 2.00	$ 1.00	$ 2.00	$ 3.00	$ 1,000.00	-
D3	$ 3.00	$ 2.00	$ 1.00	$ 2.00	$ 1,000.00	-
D4	$ 4.00	$ 3.00	$ 2.00	$ 1.00	$ 1,000.00	20,000.00
RETAILER TO DEMAND MARKET						
	DEMAND REGION Production and Transportation Cost per 1,000,000				**Fixed**	
Supply Region	Demand1	Demand2	Demand3	Demand4	**Cost ($)**	**Capacity**
R1	$ 1.00	$ 2.00	$ 3.00	$ 4.00	$ 1,000.00	20,000.00
R2	$ 2.00	$ 1.00	$ 2.00	$ 3.00	$ 1,000.00	-
R3	$ 3.00	$ 2.00	$ 1.00	$ 2.00	$ 1,000.00	-
R4	$ 4.00	$ 3.00	$ 2.00	$ 1.00	$ 1,000.00	20,000.00
Demand		20,000	20,000	-		40,000

Figure 42: Input of cost, capacities and demand for calibration problem 1.

The objective is to determine which facilities should be open and the quantity of units to flow from each to minimizes the total cost of the supply chain.

Step 2: Planning: Step-wise process to perform calibration.

1. Draw the network a diagram, properly notating all variables for the facilities, capacities, costs between nodes, quantity of products flowing between nodes and demand points. Make sure to illustrate and labels the flow variables and arrows for the inputs and outputs of at least one set of nodes between suppliers-

manufactures, manufactures-distributors and distributors-retailers.

2. Formulate the problem to minimize the total cost of the complete supply chain network.

3. Build the formulation into the Excel spreadsheet and program the optimization into Risk Solver Platform.

4. Test the simulation framework for the accuracy of the results by altering the capacity and demand input values to ensure the outcomes are as expected.

Step 3: Calibration Results

The result for the calibration problem should match the following output.

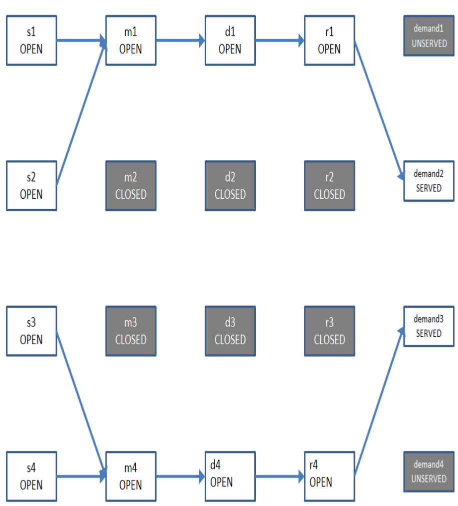


Figure 43: Calibration 01 network.

Facility	Status
s1	OPEN
s2	OPEN
s3	OPEN
s4	OPEN
m1	OPEN
m2	CLOSED
m3	CLOSED
m4	OPEN
d1	OPEN
d2	CLOSED
d3	CLOSED
d4	OPEN
r1	OPEN
r2	CLOSED
r3	CLOSED
r4	OPEN
demand1	UNSERVED
demand2	SERVED
demand3	SERVED
demand4	UNSERVED

Table 18: Calibration 01 status.

The objective function yields a $TC = \$230,000$

5.2 Calibration 02

Step 1: Problem Input values A manufacturer has four sites (m_1, m_2, m_3, m_4), each with fixed infrastructure cost of $1,000 and capacity of 10,000 units. Each manufacturer is served by four separate suppliers (s_1, s_2, s_3, s_4), and delivers products to four distributors (d_1, d_2, d_3, d_4), which in-turn deliver products to four retailers (r_1, r_2, r_3, r_4). Transportation costs between all the facilities shares the following structure cost/unit($).

	Facility 1	Facility 2	Facility 3	Facility4
Facility 1	$1	$2	$3	$4
Facility 2	$2	$1	$2	$3
Facility 3	$3	$2	$1	$2
Facility 4	$4	$3	$2	$1

Table 19: Transportation costs between all the facilities.

Capacity (maximum quantity of units output) for each facility and the demand regions:

Type	Capacity(units)			
	S_1	S_2	S_3	S_4
Supplier	10000	10000	10000	10000
	M_1	M_2	M_3	M_4
Manufacturer	0	20000	20000	0
	D_1	D_2	D_3	D_4
Distributor	0	20000	20000	0
	R_1	R_2	R_3	R_4
Retailer	0	20000	20000	0
	$\mathfrak{D}_1$	$\mathfrak{D}_2$	$\mathfrak{D}_3$	$\mathfrak{D}_4$
Demand Region	10000	10000	10000	10000

Table 20: Maximum capacity of each facility.

In the Figure 44 is shown an example of the "Inputs-costs,capacities,demand Excel worksheet entry form" in which regions 1, 2, 3, and 4 equally have 10,000 *units/year*.

Inputs - Costs, Capcaities, Demand

SUPPLIER TO MANUFACTURER PLANT

	DEMAND REGION				Fixed	
Supply Region	M1	M2	M3	M4	Cost ($)	Capacity
S1	$ 1	$ 2	$ 3	$ 4	$ 1,000	10,000
S2	$ 2	$ 1	$ 2	$ 3	$ 1,000	10,000
S3	$ 3	$ 2	$ 1	$ 2	$ 1,000	10,000
S4	$ 4	$ 3	$ 2	$ 1	$ 1,000	10,000

100%

MANUFACTURER TO DISTRIBUTOR

	DEMAND REGION				Fixed	
Supply Region	D1	D2	D3	D4	Cost ($)	Capacity
M1	$ 1	$ 2	$ 3	$ 4	$ 1,000	-
M2	$ 2	$ 1	$ 2	$ 3	$ 1,000	20,000
M3	$ 3	$ 2	$ 1	$ 2	$ 1,000	20,000
M4	$ 4	$ 3	$ 2	$ 1	$ 1,000	-

DISTRIBUTOR TO RETAILER

	DEMAND REGION Production and Transportation Cost per				Fixed	
Supply Region	R1	R2	R3	R4	Cost ($)	Capacity
D1	$ 1	$ 2	$ 3	$ 4	$ 1,000	-
D2	$ 2	$ 1	$ 2	$ 3	$ 1,000	20,000
D3	$ 3	$ 2	$ 1	$ 2	$ 1,000	20,000
D4	$ 4	$ 3	$ 2	$ 1	$ 1,000	-

RETAILER TO DEMAND MARKET

	DEMAND REGION				Fixed	
Supply Region	Demand1	Demand2	Demand3	Demand4	Cost ($)	Capacity
R1	$ 1	$ 2	$ 3	$ 4	$ 1,000	-
R2	$ 2	$ 1	$ 2	$ 3	$ 1,000	20,000
R3	$ 3	$ 2	$ 1	$ 2	$ 1,000	20,000
R4	$ 4	$ 3	$ 2	$ 1	$ 1,000	-

Demand	10,000	10,000	10,000	10,000		40,000

Figure 44: Input of cost, capacities and demand for calibration problem 2.

The objective is to determine which facilities should be open and the quantity of units to flow from each to minimizes the total cost of the supply chain.

Step 2: Planning Step-wise process to perform calibration:

1. Draw the network diagram properly notating all variables for the facilities, capacities, costs between nodes, quantity of products flowing between nodes and

demand points. Make sure to illustrate and labels the flow variables and arrows for the inputs and outputs of at least one set of nodes between suppliers-manufactures, manufactures-distributors and distributors-retailers

2. Formulate the problem to minimize the total cost of the complete supply chain network.

3. Build the formulation into the Excel spreadsheet and program the optimization into Risk Solver Platform.

4. Test simulation of the results by altering capacity and demand to ensure outcomes are as expected.

Step 3: Calibration Results The result for the calibration problem should match the following output.

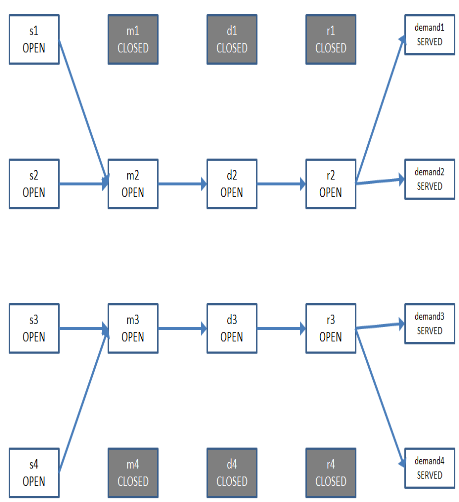


Figure 45: Calibration 02: Network.

Facility	Status
s1	OPEN
s2	OPEN
s3	OPEN
s4	OPEN
m1	CLOSED
m2	OPEN
m3	OPEN
m4	CLOSED
d1	CLOSED
d2	OPEN
d3	OPEN
d4	CLOSED
r1	CLOSED
r2	OPEN
r3	OPEN
r4	CLOSED
demand1	SERVED
demand2	SERVED
demand3	SERVED
demand4	SERVED

Table 21: Calibration 02 status.

The objective function yields a $TC = \$210,000$.

5.3 Case Study Numerical Analysis

Step 1: Implement the Monte Carlo Simulation

Step 2: Plot the CV of Supply verse CV Demand: To investigate the influence of uncertainty on the supply chain, we compute the CV of supply versus CV of demand, for ten Monte Carlo simulations, then plot the results, relative to each other with CV of supply on the y-axis and CV of demand on the x-axis. Each simulation uses an increasing uncertainty measure of the coefficient of variation of demand for the normal distribution function, of the average annual forecasted demand, $\overline{\mathfrak{D}}$. The process is summarized as follows, for each case study:

Step 2.1: Establish fixed values for the coefficient of variation of demand, $(CV)_D$.

Step 2.2: Solve the optimization and Monte Carlo simulation problem.

Step 2.3: Determine the coefficient of variation of supply, $(CV)_S$.

Step 2.4: Plot $\frac{(CV)_S}{(CV)_D}$ versus $(CV)_D$.

Step 2.5: Determine the data point at which $\frac{(CV)_S}{(CV)_D} = 1$.

Step 2.6: Plot the TC versus the data point at which $\frac{(CV)_S}{(CV)_D} = 1$.

Step 2.7: Repeat for each optimization parameter, which in our work are different values for $\overline{\mathfrak{D}}$=10000,20000,30000,40000,50000.

The outcome is two graphical plots that are used for interpretation and analysis:

(1) $\frac{(CV)_S}{(CV)_D}$ versus $(CV)_D$; and

(2) TC versus $(CV)_D$ at $\frac{(CV)_S}{(CV)_D} = 1$.

6 Results

6.1 Quantifying Uncertainty

In this section the results and numerical analysis for the Base Case and Case Study 1, 2, and 3 simulation are presented.

6.1.1 Base Case: Scenario 1 ($p = 1/3$) = Scenario 2 = Scenario 3

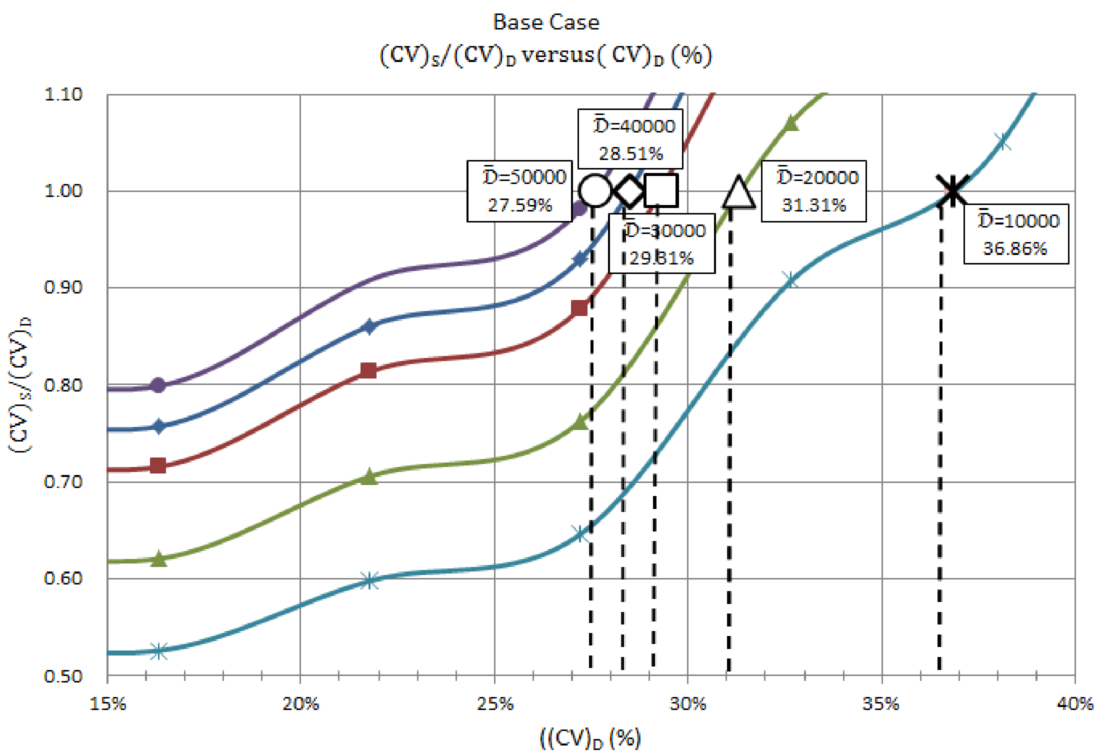


Figure 46: Base Case results.

In Figure 46 is shown the ratio of $(CV)_S/(CV)_D$ versus $(CV)_D(\%)$ for Base Case. The threshold for the maximum variation in demand that can be tolerated to maintain good coordination in an SCN is defined by $(CV)_S/(CV)_D = 1$ and identified by the hollow line markers. Utilizing the $(CV)_D(\%)$ data points values at $(CV)_D = 1$ for each average annual demand, $\overline{\mathfrak{D}}$, the plot of the relationships between $TC(\$)$ versus $(CV)_D(\%)$ is plotted in the summary of results, Figure 50.

6.1.2 Case 1: "High" (Scenario 1: $p = 100\%$)

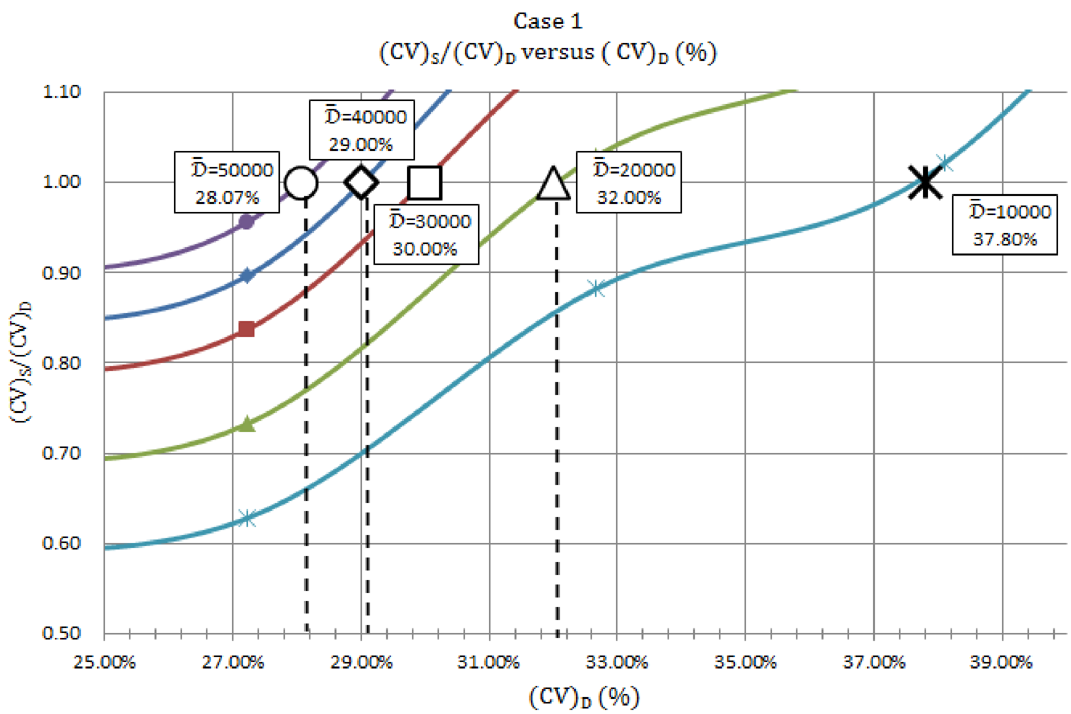


Figure 47: Case 1 results.

In Figure 47 is shown the ratio of ${}^{(CV)_S}/_{(CV)_D}$ versus $(CV)_D(\%)$ for Case 1. The threshold for the maximum variation in demand that can be tolerated to maintain good coordination in an SCN is defined by ${}^{(CV)_S}/_{(CV)_D} = 1$ and identified by the hollow data point markers. Utilizing the $(CV)_D(\%)$ data points values at $(CV)_D = 1$ for each average annual demand, $\overline{\mathfrak{D}}$, the plot of the relationships between $TC(\$)$ versus $(CV)_D(\%)$ is plotted in the summary of results, Figure 50.

6.1.3 Case 2: "Nominal" (Scenario 2: $p = 100\%$)

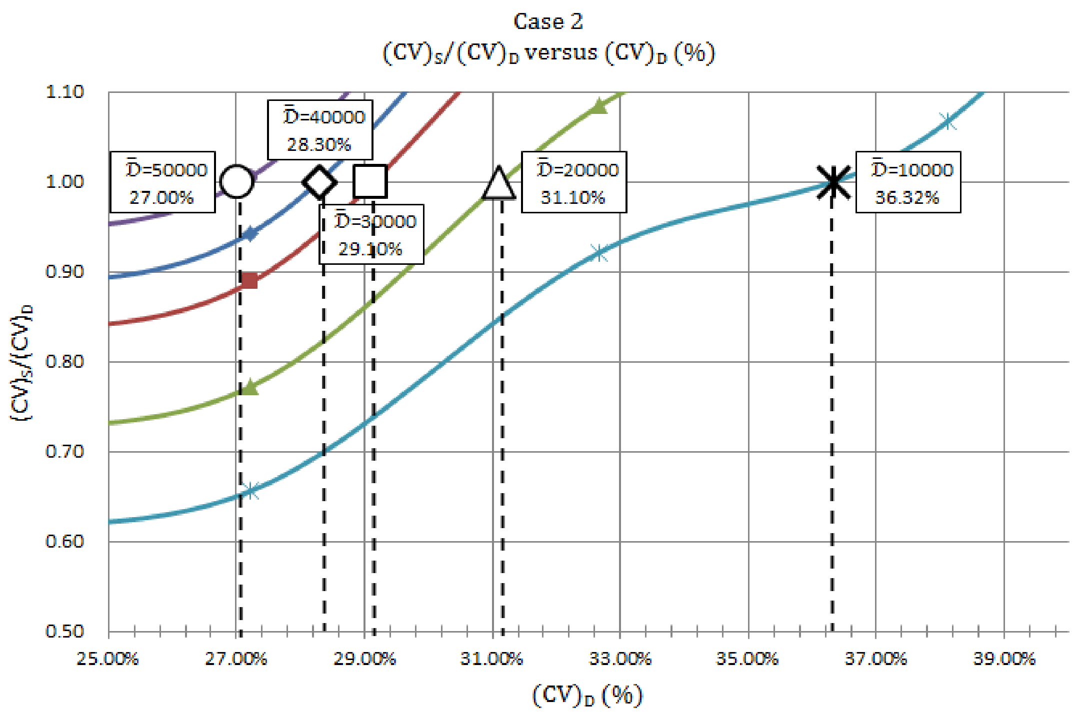


Figure 48: Case 2 results.

In Figure 48 is shown the ratio of $^{(CV)_S}/_{(CV)_D}$ versus $(CV)_D(\%)$ for Case 2. The threshold for the maximum variation in demand that can be tolerated to maintain good coordination in an SCN is defined by $^{(CV)_S}/_{(CV)_D} = 1$ and identified by the hollow data point markers. Utilizing the $(CV)_D(\%)$ data points values at $(CV)_D = 1$ for each average annual demand, $\overline{\mathfrak{D}}$, the plot of the relationships between $TC(\$)$ versus $(CV)_D(\%)$ is plotted in the summary of results, Figure 50.

6.1.4 Case 3: "Low" (Scenario 3: $p = 100\%$)

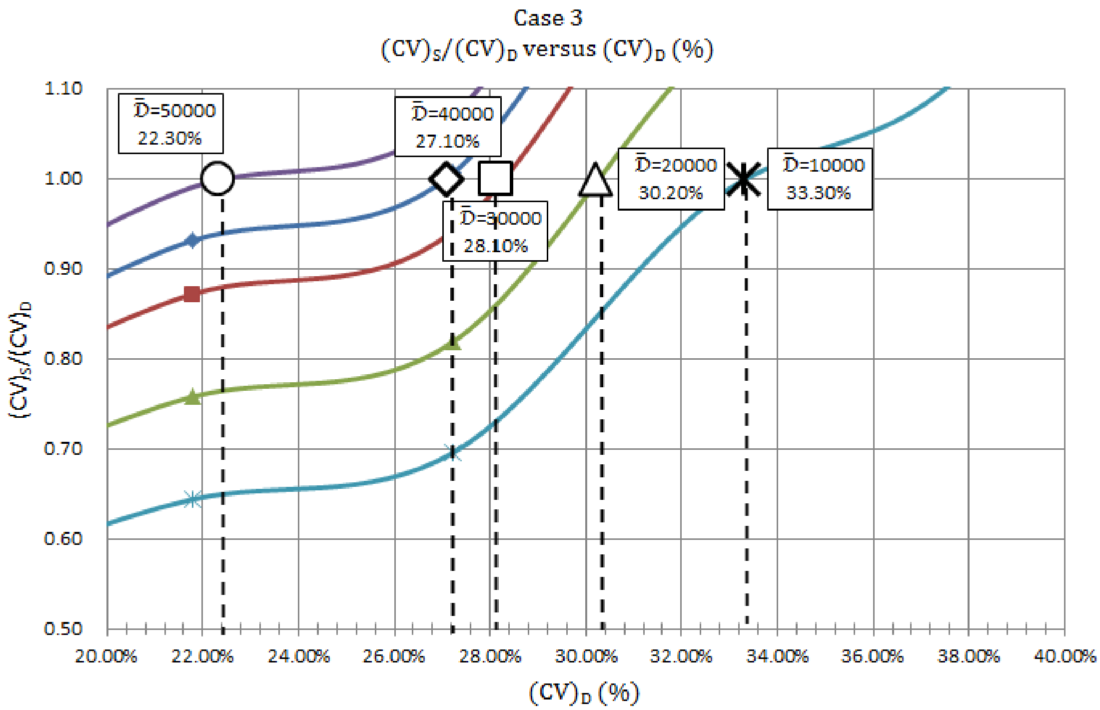


Figure 49: Case 3 results.

In Figure 49 is shown the ratio of $^{(CV)_S}/_{(CV)_D}$ versus $(CV)_D(\%)$ for Case 3. The threshold for the maximum variation in demand that can be tolerated to maintain good coordination in an SCN is defined by $^{(CV)_S}/_{(CV)_D} = 1$ and identified by the hollow data point markers. Utilizing the $(CV)_D(\%)$ data points values at $(CV)_D = 1$ for each average annual demand, $\overline{\mathfrak{D}}$, the plot of the relationships between $TC(\$)$ versus $(CV)_D(\%)$ is plotted in the summary of results, Figure 50.

6.2 Quantifying Total Cost versus $(CV)_D(\%)$

Shown in Figure 50 is the relationship of the threshold of the maximum variation in demand,$(CV)_D(\%)$, that can be tolerated to maintain coodination versus the total cost,TC, for each average annual demand, $\overline{\mathfrak{D}}$, for the Base Case and Case 1, 2 and 3 when using the integrated framework. In addition, are shown the comparative results (the solid markers) of the corresponding heuristic approach results, when utilizing the $(CV)_D(\%)$ value of the corresponding integrated framework case. The heuristic results were attained by utilizing the data point value of $(CV)_D(\%)$ and the average annual regional demand, $\overline{\mathfrak{D}}$, in the deterministic version of the framework, using a Simplex approach to solving the problem.

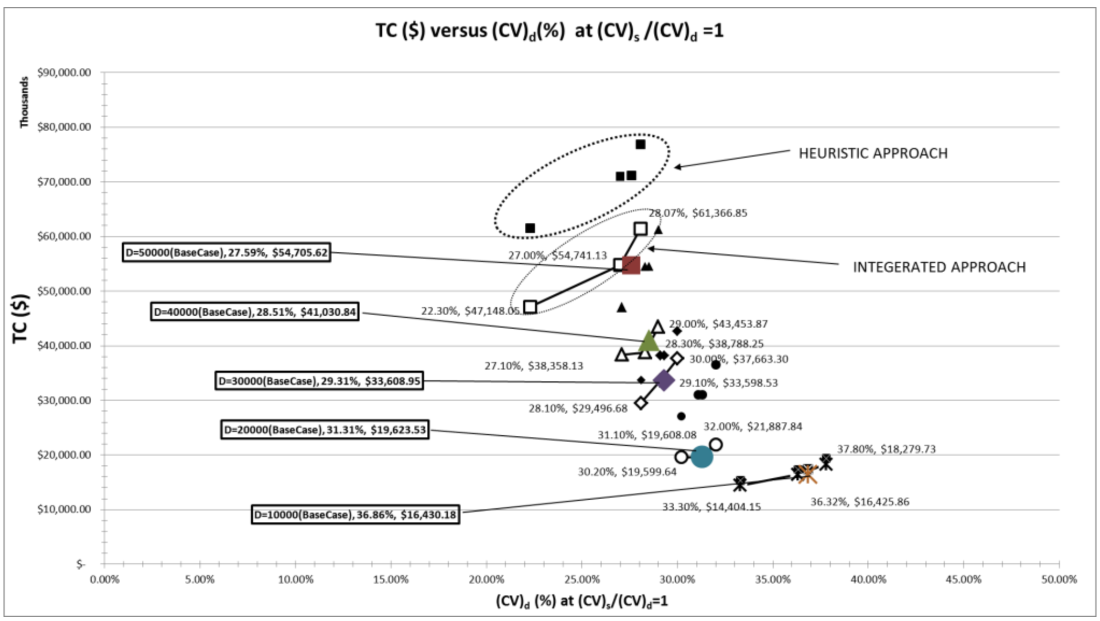


Figure 50: Total cost versus $(CV)_D(\%)$.

From Figure 50 we learn that as the average annual regional demand, $\overline{\mathfrak{D}}$ increases, while the maximum facility supply capacity remains fixed, the following are the observations:

(1) The Base Case (all scenarios are equally like to occur) results are nearly equal to the Case 2 when only the nominal scenario, s_2.

(2) The $(CV)_D(\%)$ threshold, for maintaining good supply in the supply chain network, is decreasing. In keeping the maximum supply capacity fixed in the facilities and increasing the units of measure for the $(CV)_D(\%)$, the result is that at higher levels of demand the threshold of maintaining the $(CV)_D(\%)$ is decreasing. A firm needs to increase supply capacity to prevent the threshold $(CV)_D(\%)$ converging to zero.

(3) The total cost,TC, is increasing.

(4) The range between the "High" (Case 1 results) and "Low" (Case 3 results), is increasing.

(5) At high levels of demand the integrated framework developed in our work yields a result that is 23% less in total cost than the heuristic approach.

7 Conclusion and Future Work

This work presented an integrated, rapid software-prototyping, approach to simulating and quantifying a supply chain network design. Specifically, our work studied the relationship between the threshold of maintaining good coordination in a supply chain network, ${}^{(CV)_S}/_{(CV)_D} = 1$, and the total cost, $TC(\$)$, under the influence of demand uncertainty.

The integrated framework developed in our work models a supply chain's ability to maintain a good coordinated with less total cost than a heuristic approach. Specifically, at high levels of demand, the integrated framework has shown to yield a 23% reduction in total cost when compared to the heuristic approach (Section 6.2). Therefore, it is in the interest of firms that need to remain competitive in the marketplace to utilize an integrated framework, such as that developed in our work, for efficient and rapid supply chain network modeling. In our work, I have presented five key contributions.

First, an integrated framework and dashboard cockpit, using Microsoft® Excel and the Risk Solver Platform, to model a multi-echelon supply, under the influence of demand uncertainty. The software platform that was developed utilizes an integrated framework that manages the demand, inventory and network design of a supply chain. Furthermore, I presented the technique and approach for implementing Monte Carlo simulation to understand the relationship between the coefficient of variation of demand verses coefficient of variation of supply. The relationship was measured by increasing the units of measurement of the coefficient of variation of demand and to measure the result coefficient of variation of supply. The coefficient of variation in demand was increased by incrementally widening the standard deviation from the μ from 0 to $\pm 3\sigma$ of in a normal distribution function to represent the average regional demand. The software developed in this research, called "SCMTracker", serves as low-cost, high efficiency, rapid prototyping tool for simulating and optimizing the supply chain network.

For a multinational manufacturing firm, operating in different time zones, with various currencies, fluctuating markets, and heterogeneous languages, the capability to have one integrated platform is essential. Of course, as the complexity of the features increases, so does the cost. This work presented a small-scale prototyping system that is suitable for data exchange on a local area network. Yet, such a system is difficult, if not impractical, to integrate into a global web-based, platform that needs to dynamically update the information in real-time. More research into this domain is needed, especially with the latest developments in cloud computing.

As discussed with Chao (2012) of Seagate, an area of future work that can prove of value is to expand the system to support manufacturing facilities nodes across various countries and to consider multiple global supply scenarios. The reality is that large multi-national companies are consistently exploring new geographical areas for manufacturing that increase speed to market and reduce costs. Therefore, developing information technology systems that can help a business unit manager make better decisions about locating these facilities is vital to a long-term competitive strategy.

Lastly, as prescribed by Desa (2011), enabling the software system to be more quickly updated with real-time global market conditions, will allow the manufacturing firm to gain competitive advantage by delivering higher quality, real-time information, to the business unit decision managers. Therefore, building a real-time relational web-driven supply chain network simulator that considers these expansion parameters and is integrated with the supply side e-commerce systems would be essential in competitive advantage. Quantifying the rate of improvement in the speed of accurate decision making relative to fluctuations in downstream supply chain activities (i.e., Bull-whip effect) can be of value to firm that is considering investment within information technology systems. An interesting analysis would be to quantity the cost-to-benefit trade-off's of implementing a robust information technology e-commerce system to managing a supply chain.

Appendix: VBA Code for the Modules

```
'* RANY POLANY
'* M.S. Thesis
'
Sub Open_FacilitiesEntry()
'
' OpenDemand Macro
'
'
    Sheets("Facilities_Entry").Select
    Range("D2:J21").Select
    ActiveWindow.Zoom = True
    Range("E10").Select
End Sub
-----------------------------------
Sub DetermineOptimalModel()
'
' Calculates the demand
' And puts best choices in the cell
'
Dim StaticModel
Dim MovingAverageModel
Dim ExponentialModel
Dim HoltsModel
Dim WintersModel
Dim MinModel
Dim BestModel
Dim BestModelName As String
Dim Demand_Year1
Dim Demand_Year2
MinModel = Worksheets("Demand_Comparison_Forecasts").Range("E13")
```

```
StaticModel = Worksheets("Demand_Comparison_Forecasts").Range("E7")
MovingAverageModel = Worksheets("Demand_Comparison_Forecasts").Range("E9")
ExponentialModel = Worksheets("Demand_Comparison_Forecasts").Range("E10")
HoltsModel = Worksheets("Demand_Comparison_Forecasts").Range("E11")
WintersModel = Worksheets("Demand_Comparison_Forecasts").Range("E12")

' Identifies the best model using the lowest value for the MAPE
'
If MinModel = StaticModel Then
BestModelName = "Static Forcast"
BestModel = StaticModel

ElseIf MinModel = MovingAverageModel Then
BestModelName = "Moving Average"
BestModel = MovingAverage_4Month

ElseIf MinModel = ExponentialModel Then
BestModelName = "Exponential"
BestModel = ExponentialModel

ElseIf MinModel = HoltsModel Then
BestModelName = "Holts"
BestModel = HoltsModel

ElseIf MinModel = WintersModel Then
BestModelName = "Winters"
BestModel = WintersModel

End If

' Based on the determined best model, the forecasted Annual Demand is determined
```

```
'
If BestModel = StaticModel Then
Demand_Year1 = Worksheets("Demand_Comparison_Forecasts").Range("L7")
Demand_Year2 = Worksheets("Demand_Comparison_Forecasts").Range("M7")

ElseIf BestModel = MovingAverageModel Then
Demand_Year1 = Worksheets("Demand_Comparison_Forecasts").Range("L9")
Demand_Year2 = Worksheets("Demand_Comparison_Forecasts").Range("M9")

ElseIf BestModel = ExponentialModel Then
Demand_Year1 = Worksheets("Demand_Comparison_Forecasts").Range("L10")
Demand_Year2 = Worksheets("Demand_Comparison_Forecasts").Range("M10")

ElseIf BestModel = HoltsModel Then
Demand_Year1 = Worksheets("Demand_Comparison_Forecasts").Range("L11")
Demand_Year2 = Worksheets("Demand_Comparison_Forecasts").Range("M11")

ElseIf BestModel = WintersModel Then
Demand_Year1 = Worksheets("Demand_Comparison_Forecasts").Range("L12")
Demand_Year2 = Worksheets("Demand_Comparison_Forecasts").Range("M12")

End If

' Populates the cells with the Summary Results for the Demand Module
'
Range("K7") = BestModelName
Range("K8") = Demand_Year1
Range("K9") = Demand_Year2
Range("K10") = (Demand_Year1 + Demand_Year2) / 2

End Sub
```

```
-------------------------------------
Sub Open_MainModule()
'
' OpenMainModule Macro
' Opens Main Module Worksheet
'
' Keyboard Shortcut: Ctrl+m
'
    Sheets("Main").Select
    Range("E1:M41").Select
    ActiveWindow.Zoom = True
    Range("E5").Select

End Sub
Sub PrintSummary()
'
' PrintSummary Macro
' Prints Summary Worksheet
'

'
    ExecuteExcel4Macro "PRINT (1,,,1,,,,,,,,2,,, TRUE,,FALSE)"
End Sub
Sub Clear_DemandDataSummary()
'
' ClearDemandData Macro
' ClearsDemandData
'

'
    Range("K6:M9").Select
```

```
    Selection.ClearContents
End Sub
Sub Clear_InventoryManagementSummary()
'
' ClearInventoryManagement Macro
' ClearsInventoryManagement Data
'

'
    Range("K13:K25").Select
'*      Selection.ClearContents
End Sub
Sub ClearTransportationDataSummary()
'
' ClearTransportationData Macro
' Clear Transportation Data
'

'
    Range("K24:M27").Select
    Selection.ClearContents
End Sub
Sub Clear_DemandData1()
'
' Clear DemandData1 Column Macro
'

'
    Range("E4:E23").Select
    Selection.ClearContents
End Sub
```

```
-----------------------------------
Sub Clear_DemandData2()
'
' Clear DemandData2 Column Macro
'

'
    Range("F4:F23").Select
    Selection.ClearContents
End Sub
-----------------------------------
Sub Clear_DemandData3()
'
' Clear DemandData3 Column Macro
'

'
    Range("G4:G23").Select
    Selection.ClearContents
End Sub
Sub Clear_DemandData4()
'
' Clear DemandData4 Column Macro
'

'
    Range("H4:H23").Select
    Selection.ClearContents
End Sub
Sub Open_BestModel()
'
```

```
' OpenBestModel Macro
'

If BestModel = StaticModel Then
Sheets("Demand_Static_Chart").Select

ElseIf BestModel = MovingAverageModel_4Month Then
Sheets("Demand_MA_Chart").Select

ElseIf BestModel = Exponential Then
Sheets("Demand_Exponential_Chart").Select

ElseIf BestModel = HoltsModel Then
Sheets("Demand_Holts_Chart").Select

ElseIf BestModel = WintersModel Then
Sheets("Demand_Winters_Chart").Select
End If


'
End Sub
-----------------------------------
Sub ComputeInventory()
'
' Compute Inventory
'

'
Dim SelectedModel As String
Dim strModelString As String
```

```
Dim AnnualDemand As Double
Dim OptimalInventory As Double
Dim NumberofShipments As Double
Dim CycleInventory As Double
Dim CycleInventoryValue As Double
Dim OrderFrequency As Double
Dim SafetyStock As Double
Dim SafetyStockValue As Double
Dim StandardDevDuringLeadTime As Double
Dim ReOrderPoint As Double
Dim ESC As Double
Dim FillRate As Double

Dim AnnualMaterialCost As Double
Dim AnnualOrderingCost As Double
Dim AnnualHoldingCost As Double
Dim TotalAnnualCost As Double

SelectedModel = Range("K13")

If SelectedModel = "Static" Then
AnnualDemand = Worksheets("Demand_Comparison_Forecasts").Range("O7")

ElseIf SelectedModel = "Moving Average" Then
AnnualDemand = Worksheets("Demand_Comparison_Forecasts").Range("O9")

ElseIf SelectedModel = "Exponential" Then
AnnualDemand = Worksheets("Demand_Comparison_Forecasts").Range("O10")

ElseIf SelectedModel = "Holts" Then
AnnualDemand = Worksheets("Demand_Comparison_Forecasts").Range("O11")
```

```
ElseIf SelectedModel = "Winters" Then
AnnualDemand = Worksheets("Demand_Comparison_Forecasts").Range("O12")

End If

OptimalInventory = Sqr((2 * AnnualDemand * (Worksheets("Main").Range("H17"))
      / _
(((Worksheets("Main").Range("H13") * (Worksheets("Main").Range("H15")))))))

NumberofShipments = AnnualDemand / OptimalInventory
CycleInventory = OptimalInventory / 2
CycleInventoryValue = CycleInventory * (Worksheets("Main").Range("H15"))
OrderFrequency = 365 / NumberofShipments
SafetyStock = WorksheetFunction.NormSInv(Range("H19")) * Sqr(Range("H22")) *
      Range("F22")
SafetyStockValue = SafetyStock * (Worksheets("Main").Range("H15"))
StandardDevDuringLeadTime = (AnnualDemand / 52) * ((Worksheets("Main").
      Range("F25")) * (Sqr((Worksheets("Main").Range("H22")))))
ReOrderPoint = SafetyStock + (AnnualDemand / 52) * ((Worksheets("Main").Range
      ("H22")))

With Application.WorksheetFunction
ESC = (-1) * SafetyStock * (1 - .NormDist(SafetyStock /
      StandardDevDuringLeadTime, 0, 1, 1)) + StandardDevDuringLeadTime * .
      NormDist((SafetyStock / StandardDevDuringLeadTime), 0, 1, 0)
End With

FillRate = 1 - ESC / OptimalInventory
```

```
AnnualMaterialCost = AnnualDemand * Worksheets("Main").Range("H15")
AnnualOrderingCost = (AnnualDemand / OptimalInventory) * (Worksheets("Main").
    Range("H17"))
AnnualHoldingCost = (OptimalInventory / 2) * ((Worksheets("Main").Range("H13")
    )) * (Worksheets("Main").Range("H15"))
TotalAnnualCost = AnnualMaterialCost + AnnualOrderingCost +
    AnnualHoldingCost

Range("K14") = OptimalInventory
Range("K15") = NumberofShipments
Range("K16") = CycleInventory
Range("K17") = CycleInventoryValue

Range("K18") = OrderFrequency

Range("K19") = SafetyStock
Range("K20") = SafetyStockValue
Range("K21") = StandardDevDuringLeadTime
Range("K22") = ReOrderPoint
Range("K23") = ESC
Range("K24") = FillRate



Range("K26") = AnnualMaterialCost
Range("K27") = AnnualOrderingCost
Range("K28") = AnnualHoldingCost
Range("K29") = TotalAnnualCost



End Sub
-----------------------------------
```

```
Sub OpenWinters()
'
' OpenWinters Macro
' Opens Winters Model
'

'
    Sheets("Demand_Winters_Data").Select
    Range("B3:O36").Select
    ActiveWindow.Zoom = True
End Sub
Sub OpenHolts()
'
' OpenHolts Macro
' Opens Holts Model
'

'
    Sheets("Demand_Holts_Data").Select
    Range("B3:N35").Select
    ActiveWindow.Zoom = True
    Range("B3").Select
End Sub
Sub OpenExponential()
'
' OpenExponential Macro
' Opens Exponential Model
'

'
```

```
    Sheets("Demand_Exponential_Data").Select
     Range("B3:M35").Select
    ActiveWindow.Zoom = True
    Range("B3").Select
End Sub
Sub OpenMovingAverage()
'
' OpenMovingAverage Macro
' Opens Moving Average Analysis

'

    Sheets("Demand_MA_Data").Select
    Range("B3:M34").Select
    ActiveWindow.Zoom = True
    Range("B3").Select
End Sub
-----------------------------------
Sub OpenStatic()
'
' OpenStatic Macro
' Opens Static Forecasting Analysis
'

'
    Sheets("Demand_Static_Data").Select
    Range("B3:P35").Select
    ActiveWindow.Zoom = True
    Range("B3").Select
End Sub
-----------------------------------
```

```
Sub Clear_Step1()
'
' ClearStep1 Macro
'

'
    Range("K7:M10").Select
    Selection.ClearContents
End Sub
-----------------------------------
Sub Clear_Step2()
'
' Clear_Step2 Macro
'

'
    Range("K13:M26").Select
    Selection.ClearContents
End Sub
-----------------------------------
Sub Clear_Step3()
'
' Clear_Step4 Macro
'

'
    Range("K28:M31").Select
    Selection.ClearContents
End Sub
-----------------------------------
Sub Clear_Step4()
```

```
'
' Clear_Step4 Macro
'


'
    Range("K37:M40").Select
    Selection.ClearContents
End Sub
Sub ViewBestModel()

If Range("K7") = "Static Forcast" Then
Sheets("TeleComOptic_P01_Static").Select

ElseIf Range("K7") = "MovingAverage_4Month" Then
Sheets("TeleComOptic_P01_Static").Select

ElseIf Range("K7") = "MovingAverage_3Month" Then
Sheets("TeleComOptic_P01_Static").Select

ElseIf Range("K7") = "Exponential" Then
Sheets("TeleComOptic_P01_Static").Select

ElseIf Range("K7") = "Holts" Then
Sheets("TeleComOptic_P01_Static").Select
ElseIf Range("K7") = "Winters" Then
Sheets("TeleComOptic_P01_Static").Select
End If



End Sub
-----------------------------------
```

```
Sub OpenMAPE()
'
' OpenMAPE Macro
' Opens MAPE Analysis
'

'
    Sheets("Plot_of_MAPE").Select
End Sub
Sub OpenFacilitiesDesign_()
'
' OpenFacilitiesDesign Macro
' Open Facilities Design
'

'
    Sheets("Facilities_Design").Select
    Range("A1:K27").Select
    ActiveWindow.Zoom = True
End Sub
-----------------------------------
Sub Compute_FacilitiesDesign()
'
' Populates the Facilities with the Information after running Solver
' Reference MSDN: http://support.microsoft.com/kb/843304#5
'
'

' Clear Prior Data in the cells
'Sheets("Facilities_Design_Optimizer").Select
'Range("D43:G46").Select
```

```
'Selection.ClearContents

'Sheets("Facilities_Design_Optimizer").Select
'Range("D51:G54").Select
'Selection.ClearContents

'Sheets("Facilities_Design_Optimizer").Select
'Range("D60:G63").Select
'Selection.ClearContents

'Sheets("Facilities_Design_Optimizer").Select
'Range("D68:G71").Select
'Selection.ClearContents

DetermineOptimalModel

Sheets("Facilities_Design_Optimizer").Select

Range("O42:S45").Select
    Application.CutCopyMode = False
    Selection.Copy
    Range("D43").Select
    ActiveSheet.Paste
    Range("D51").Select
    ActiveSheet.Paste
    Range("D60").Select
    ActiveSheet.Paste
    Range("D68").Select
    ActiveSheet.Paste

' Set Solver parameters
```

```
SolverReset
SolverOptions Precision:=0.000001
SolverOptions Convergence:=0.0001
SolverOptions AssumeLinear:=True
SolverOptions MaxTime:=150
SolverOptions Iterations:=250
SolverOptions AssumeNonNeg:=True

'AssumeLinear:=True, StepThru:=False, Estimates:=1, Derivatives:=1, _
'SearchOption:=1, IntTolerance:=1, Scaling:=False, Convergence:=0.001, _
'AssumeNonNeg:=False



SolverOK SetCell:=Worksheets("Facilities_Design_Optimizer").Range("D112"),
    MaxMinVal:=2, _
ByChange:=Worksheets("Facilities_Design_Optimizer").Range("D43:H46,D51:H54,D60
    :H63,D68:H71")

'SolverOK SetCell:=Range("A2"), MaxMinVal:=3, ValueOf:=50, _
  '        ByChange:=Range("A1")



' Set Solve Constraints

'# Relation can be a value between 1 and 5 as in the following example:
' * The value 1 is less than or equal to (<=).
' * The vaue 2 is equal to (=).
' * The value 3 is greater than or equal to (>=).
' * The value 4 is an integer.
' * The value 5 is the binary (a value of zero or one).
```

```
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$A$43:$A$46
    "), Relation:=3, FormulaText:="$J$43:$J$46"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$A$51:$A$54
    "), Relation:=3, FormulaText:="$J$51:$J$54"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$A$60:$A$63
    "), Relation:=3, FormulaText:="$J$60:$J$63"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$A$68:$A$71
    "), Relation:=3, FormulaText:="$I$68:$I$71"



'Decision Variables
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$43:$G$46
    "), Relation:=3, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$51:$G$54
    "), Relation:=3, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$60:$G$63
    "), Relation:=3, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$68:$G$71
    "), Relation:=3, FormulaText:="0"

SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$72:$G$72
    "), Relation:=2, FormulaText:="$D$38:$G$38"

'Constraints
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$77:$D$80
    "), Relation:=3, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$85:$D$88
    "), Relation:=3, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$94:$D$97
    "), Relation:=3, FormulaText:="0"
```

```
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$102:
    $D$105"), Relation:=3, FormulaText:="0"

'SolverAdd CellRef:=worksheets("Facilities_Design_Optimizer").Range("$H$38"),
    Relation:=2, FormulaText:="$J$47"
'SolverAdd CellRef:=worksheets("Facilities_Design_Optimizer").Range("$H$38"),
    Relation:=2, FormulaText:="$J$55"
'SolverAdd CellRef:=worksheets("Facilities_Design_Optimizer").Range("$H$38"),
    Relation:=2, FormulaText:="$J$63"

SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$H$38"),
    Relation:=2, FormulaText:="$J$72"

SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$H$43:$H$46
    "), Relation:=5, FormulaText:="binary"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$H$51:$H$54
    "), Relation:=5, FormulaText:="binary"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$H$60:$H$63
    "), Relation:=5, FormulaText:="binary"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$H$68:$H$71
    "), Relation:=5, FormulaText:="binary"

SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$107:$G$107
    "), Relation:=2, FormulaText:="$H$38"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$D$109:
    $G$109"), Relation:=2, FormulaText:="0"



SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$43:$I$46"),
     Relation:=3, FormulaText:="$J$43:$J$46"
```

```
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$51:$I$54"),
        Relation:=3, FormulaText:="$J$51:$J$54"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$60:$I$63"),
        Relation:=3, FormulaText:="$J$60:$J$63"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$68:$I$71"),
        Relation:=3, FormulaText:="$J$68:$J$71"

SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$78"),
       Relation:=2, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$86"),
       Relation:=2, FormulaText:="0"
SolverAdd CellRef:=Worksheets("Facilities_Design_Optimizer").Range("$I$95"),
       Relation:=2, FormulaText:="0"

' Finish and do not display the results
SolverSolve UserFinish:=True

' Finish and keep the results
SolverFinish KeepFinal:=1

Sheets("Facilities_Network_Mapper").Select
Module7.DeleteAllShapes
Module7.DrawRect

Sheets("Main").Select
Range("K32").Select

Module7.Determine_Open_Closed_Facilities

End Sub
------------------------------------
```

```
Sub Populuate_Facilities_Info ()
If Worksheets("Facilities_Design").Range("G13") >= 1 Then
Worksheets("Main").Range("K28") = "Use Low Capacity"

ElseIf Worksheets("Facilities_Design").Range("H13") >= 1 Then
Worksheets("Main").Range("K28") = "Use High Capacity Plant"

ElseIf Worksheets("Facilities_Design").Range("G13") + Worksheets("
    Facilities_Design").Range("H13") = 0 Then
Worksheets("Main").Range("K28") = "Eliminate Factory"
End If



'* Determine Facilities for Shanghai

If Worksheets("Facilities_Design").Range("G14") >= 1 Then
Worksheets("Main").Range("K29") = "Use Low Capacity Plant"

ElseIf Worksheets("Facilities_Design").Range("H14") >= 1 Then
Worksheets("Main").Range("K29") = "Use High Capacity Plant"

ElseIf Worksheets("Facilities_Design").Range("G14") + Worksheets("
    Facilities_Design").Range("H14") = 0 Then
Worksheets("Main").Range("K29") = "Eliminate Factory"
End If

'* Determine Facilities for Ningbo
If Worksheets("Facilities_Design").Range("G15") >= 1 Then
Worksheets("Main").Range("K30") = "Use Low Capacity Plant"
```

```
ElseIf Worksheets("Facilities_Design").Range("H15") >= 1 Then
Worksheets("Main").Range("K30") = "Use High Capacity Plant"

ElseIf Worksheets("Facilities_Design").Range("G15") + Worksheets("
    Facilities_Design").Range("H15") = 0 Then
Worksheets("Main").Range("K30") = "Eliminate Factory"
End If



Worksheets("Main").Range("K31") = Worksheets("Facilities_Design").Range("C19")
    + Worksheets("Facilities_Design").Range("C20") + Worksheets("Facilities_Design
    ").Range("C21")

Worksheets("Main").Range("K32") = Worksheets("Facilities_Design").Range("C26")
End Sub
-----------------------------------



Sub ComputeTransportation()

Dim SupplierADeliveryDays As Double
Dim SupplierBDeliveryDays As Double
Dim SupplierCDeliveryDays As Double
Dim SupplierDDeliveryDays As Double
Dim SupplierEDeliveryDays As Double

Dim SupplierATotalCost As Double
Dim SupplierBTotalCost As Double
Dim SupplierCTotalCost As Double
Dim SupplierDTotalCost As Double
Dim SupplierETotalCost As Double
```

```
Dim PreferredSupplier As String
Dim PreferredMode As String
Dim MinimizedTotalCost As Double
Dim DaysToDelivery As Double

SupplierADeliveryDays = Worksheets("TransportationTotalCosts").Range("A13")
SupplierBDeliveryDays = Worksheets("TransportationTotalCosts").Range("A14")
SupplierCDeliveryDays = Worksheets("TransportationTotalCosts").Range("A15")
SupplierDDeliveryDays = Worksheets("TransportationTotalCosts").Range("A16")
SupplierEDeliveryDays = Worksheets("TransportationTotalCosts").Range("A17")

SupplierATotalCost = Worksheets("TransportationTotalCosts").Range("M13")
SupplierBTotalCost = Worksheets("TransportationTotalCosts").Range("M14")
SupplierCTotalCost = Worksheets("TransportationTotalCosts").Range("M15")
SupplierDTotalCost = Worksheets("TransportationTotalCosts").Range("M16")
SupplierETotalCost = Worksheets("TransportationTotalCosts").Range("M17")

If Worksheets("TransportationTotalCosts").Range("M18") = SupplierATotalCost
    Then
PreferredSupplier = "Supplier A"
PreferredMode = Worksheets("TransportationTotalCosts").Range("C13")
MinimizedTotalCost = Worksheets("TransportationTotalCosts").Range("M13")
DaysToDelivery = SupplierADeliveryDays


ElseIf Worksheets("TransportationTotalCosts").Range("M18") = SupplierBTotalCost
    Then
PreferredSupplier = "Supplier B"
PreferredMode = Worksheets("TransportationTotalCosts").Range("C14")
MinimizedTotalCost = Worksheets("TransportationTotalCosts").Range("M14")
```

```
DaysToDelivery = SupplierBDeliveryDays

ElseIf Worksheets(”TransportationTotalCosts”).Range(”M18”) = SupplierCTotalCost
    Then
PreferredSupplier = ”Supplier C”
PreferredMode = Worksheets(”TransportationTotalCosts”).Range(”C15”)
MinimizedTotalCost = Worksheets(”TransportationTotalCosts”).Range(”M15”)
DaysToDelivery = SupplierCDeliveryDays



ElseIf Worksheets(”TransportationTotalCosts”).Range(”M18”) = SupplierDTotalCost
    Then
PreferredSupplier = ”Supplier D”
PreferredMode = Worksheets(”TransportationTotalCosts”).Range(”C16”)
MinimizedTotalCost = Worksheets(”TransportationTotalCosts”).Range(”M16”)
DaysToDelivery = SupplierDDeliveryDays



ElseIf Worksheets(”TransportationTotalCosts”).Range(”M18”) = SupplierETotalCost
    Then
PreferredSupplier = ”Supplier E”
PreferredMode = Worksheets(”TransportationTotalCosts”).Range(”C17”)
MinimizedTotalCost = Worksheets(”TransportationTotalCosts”).Range(”M17”)
DaysToDelivery = SupplierEDeliveryDays



End If

Range(”K35”) = PreferredSupplier
Range(”K36”) = PreferredMode
Range(”K37”) = MinimizedTotalCost
```

```
Range("K38") = DaysToDelivery


End Sub
-----------------------------------
Sub ClearTransportationSummary()
'
' ClearTransportationData Macro
' Clear Transportation Data
'


'
    Range("K35:M38").Select
    Selection.ClearContents
End Sub
```

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