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Modeling the environmental impact of demand variability upon supply chains in the beverage industry

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MODELING THE ENVIRONMENTAL IMPACT OF DEMAND VARIABILITY UPON SUPPLY CHAINS IN THE BEVERAGE INDUSTRY

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ABSTRACT

High demand variability can produce several inefficiencies in the supply chain, increasing cost and decreasing service level. This research focuses on the environmental impact of demand variability on supply chains especially in the beverage industry by investigating the relationship between demand variability and the emissions of carbon dioxide. The analysis was based on a beverage industry case, considering a two-stage supply chain. A simulation model was developed to represent the supply chain. The experimental factors demand variability, demand level, forecast method, system size, and truck fleet configuration were manipulated in order to represent different scenarios. A statistical Design of Experiment (DOE) model was used to understand the impact of these factors in relation to the emissions of carbon dioxide, cost and service level. The findings suggest that increments in demand variability result in an increment in carbon dioxide emissions due to the distribution of product. It was also observed that an increment in demand variability results in an increment in cost and a decrease in service level. The study also suggests that the factors that influence demand level and truck fleet configuration have a significant impact on the amount of carbon dioxide emissions. A significant interaction between demand variability and demand level was also identified in relation to carbon dioxide emissions, cost, and service level. Trade-offs were identified between carbon dioxide emissions and service level as well as between cost and service level.

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1. INTRODUCTION

The U.S. accounts for approximately 21% of the world total carbon dioxide emissions. In 2006, 26.1 % of the total greenhouse gases emitted by the U.S. were produced by the transportation sector (EPA 2007). Considering that the transportation sector is an important contributor to the total emissions of carbon dioxide, as well as the fastest growing carbon dioxide emitter, it is important to study the factors that might cause an increment in emissions in this sector. Companies are assuming more and more environmental responsibility, giving increasing importance to the amount of greenhouse gases produced by their operations. Furthermore, with the distribution of product to the customers, companies strongly contribute to the emissions of carbon dioxide accounted to the transportation sector.

Demand variability refers to how spread-out or tightly-clustered is the demand from the customer. Companies faced with high demand variability are likely to have an increase in cost and decrease in service level. In addition, could it be likely that high demand variability may also result in increased carbon dioxide emissions due to the incremental demand in transportation required for product delivery? This study strives to answer that important question.

This research incorporates the areas of supply chain management, environmental impact and distribution systems, amongst others. It is expected that the reader of this study will gain a better understanding of the impact that demand variability may have on carbon dioxide emissions as well as other factors like demand level and truck fleet configuration that may increase the impact. The specific conclusions presented here apply to companies in the beverage industry that distribute product to different retailers, but

may also be applicable to companies in other sectors dependent on truck distribution systems.

The next section of this paper explains the problem statement and objective of this research. The third section examines the literature related to transportation and carbon dioxide emissions; supply chain, and simulation. Section four concentrates on the supply chain design, the creation of the simulation model, the model assumptions, and the design of the statistical experiment. The next section presents and analyzes the results of the statistical experiment. The conclusions and an explanation of future research are shown in the last section.

2. PROBLEM STATEMENT

Supply chains react in different ways to customer demand variability. In some cases, the supply chain is very sensitive to changes in demand pattern from the customer. Besides the variability introduced to the system by the customer, other factors in the supply chain may contribute to the amplification of demand variability upstream the supply chain.

High levels of demand variability may cause increased levels of activity (i.e. paperwork, overtime, longer production runs, picking and warehousing operations, and distribution) in an effort to maintain high levels of customer satisfaction. This may result in increased cost and lower service level for the wholesaler. When facing uncertain or highly variable demand, some businesses with sensitive products and deadlines (such as in the food and beverage industry), or in highly competitive markets, may place additional emphasis on being responsive and maintaining high service levels. This requires an efficient management of the overall supply chain including appropriate inventory controls, information systems, and a somewhat flexible distribution fleet, amongst others.

However, when a higher service level is pursued, more frequent transportation may be required. Increased transportation may be a consequence of an increase in order volume, multiple shipments of partial orders, or simply the response to an augment in demand with unchanged schedules and due dates. In addition to the traditional fuel, labor, and maintenance cost considerations, additional transportation will cause added environmental impacts in the form of greenhouse gases (mostly carbon dioxide) emissions, criteria pollutants (NOx, SOx, etc.), amongst others. These emissions impact

the environment in different ways and degrees: global warming, ozone depletion, and human health to mention some.

2.1 Objective

In this work, a model that investigates and quantifies the environmental impact of increased transportation in the supply chain is developed. The model helps explore the relationships between demand variability and carbon dioxide emissions associated with the increased fleet activity. The analysis was performed for several different scenarios. A case study is developed around a specific scenario in a local beverage wholesaler in Rochester, N.Y. The purpose of this research is to test the hypothesis that an increase in demand variability causes an increase in transportation therefore increasing carbon dioxide emissions.

3 LITERATURE REVIEW

3.1 Transportation and Carbon Dioxide Emissions

Transportation is the fastest growing carbon dioxide emitter (Schipper 2008). Therefore more attention should be placed into measuring the emissions produced by the transportation sector. Weber et al. (2007) reinforces that the carbon foot print of the U.S. has expanded and points out that the sectors of international transport and wholesaling are usually ignored when calculating emissions even though they represent a significant portion of the total emissions. A way to calculate the emissions produced by the transportation sector is to use fuel sales, multiplying the number of gallons sold by the average emissions per gallon. Individual information on vehicles, usage and CO_2 emissions per kilometer is limited. Hendrickson et al. (2006) analyzed the U.S. transportation service sectors of air, rail, water, truck, transit and pipeline in relation to economic impact, energy and GHG emissions. The study concluded that truck transportation is the most energy intensive of the transportation modes per ton-mile of service.

There is a general need for integrated analytical tools in order to quantify cost, time of delivery, energy and emissions of freight transportation networks (Corbett and Winebrake 2007). Many researchers take an environmental approach to the analysis of the impact of decision making in supply chain networks. Winebrake (2008) introduces an energy and environmental network optimization model using an intermodal freight network which identifies optimal routes in order to meet objectives (e.g. minimize carbon dioxide emissions). Falzarano (2007) illustrates the development of Intermodal Freight transportation networks and their limitations using the software ArcGIS Network

Analyst. Nagurney and Toyasaki (2003) developed an algorithm that determined product shipments and calculated the emissions generated using several supply chain examples. Reich-Weiser and Dornfeld (2008) introduced a tool to calculate the environmental impact of manufacturing supply chains.

With the increase in transportation due to globalization, the need to measure and compare carbon dioxide emissions in supply chains is becoming critical (Cordeiro 2008). In order to measure the emissions of carbon dioxide due to transportation using diesel engine trucks, two methods were considered. The Environmental Protection Agency (EPA), "Emission Facts" report from the Office of Transportation and Air Quality, developed several fact sheets that enable the calculation of average emission of greenhouse gases based on the consumption of a gallon of fuel, either gasoline or diesel (EPA 2005). The emissions calculation is based on grams of carbon content per gallon of gasoline or diesel, oxidation factor and molecular weight of carbon, resulting in 10.1 kilograms of carbon dioxide per gallon of diesel (EPA 2005). When calculating other greenhouse gases like nitrogen oxide or sulfur oxide, the only different parameter is the molecular weight. The Revised 1996 Intergovernmental Panel on Climate Change Guidelines for National Greenhouse Gas Inventories, measures the estimated emissions factor for US Heavy Duty Diesel Vehicles. The calculations result in an average of 1.01 kilograms of carbon dioxide per kilometer (IPCC 1997). The work performed here requires that the carbon dioxide emissions are calculated based on gallons of diesel consumed rather than number of miles traveled, for this reason this study used the calculations defined by the EPA in order to calculate carbon dioxide emissions.

3.2 Simulation

Simulation has been identified as "one of the breakthrough technologies that will accelerate the grand challenges facing manufacturing in 2020" (Bansal 2002). Bansal has identified some constraints for the use of computer simulation: few programmers, time consuming, and probability of erroneous results. Modeling the supply chain enables companies to save time and money by studying, "As Is" and "What If" scenarios like inventory policies, layouts, forecasting methods, and processes improvements. Simulation models give support to the decision making, reducing risk and cost. For this reason, analysts are starting to use it as a tool to verify and propose solutions (Vieira 2004).

Kleijnen (2005) discussed sensitivity and robustness analysis, validation, and verification techniques for simulation models. Additionally, an explanation of the most common simulation types used for supply chain management is presented:

Spreadsheet simulation: Commonly used to implement manufacturing resources planning. The ability to graphically simulate the model is one of the reasons why the discrete-event dynamic system (DEDS) simulation was used in this study over spreadsheet simulation.

System Dynamics (SD): Developed by Forrester, this tool provides a more realistic model than spreadsheet simulation (Forrester 1958). Although SD models have been used to simulate supply chains fairly well, the user friendly interface of DEDS simulation makes it a preferred tool for this study.

Business games: This simulation tool models human behavior by letting the managers themselves input data and interact with the simulation. It is more interactive than the

other tools but it does not apply for the purposes of this research because there is no data required to be inputted.

Discrete-event dynamic system (DEDS) simulation: This tool has two characteristics which differentiates it from the other tools. First, it represents individual events and second, it incorporates uncertainties. This simulation can introduce random events in the simulation; this is one of the reasons why it is one of the best tools to simulate systems in which variability is a key factor. Discrete-event dynamic system simulation was used in this study mostly due to the ease of introducing variability and its user friendly interface. Discrete event simulation permits the evaluation of operating performance prior to implementation (Chang and Makatsoris 2001). Discrete event simulation, helps understand the overall supply chain, capture system dynamics, and minimize risk in the planning process with the use of "What If" scenarios (Chang and Makatsoris 2001).

3.3 Supply Chain and Simulation

Supply chain management is a key factor for the success of a company. An example of the application of simulation for the analysis of supply chains is the Supply Chain Analyzer (SCA) developed by IBM (Banks 2002). Its main purpose was to perform strategic studies related to number and location of manufacturers, stocking levels, replenishment policies, distribution policies, lead times, supplier performance and demand variability (Banks et al. 2002).

The literature shows that other researchers like Jain and Leong (2005) and Vieira (2004) have also used the simulation software package ARENA to analyze the behavior of supply chains. Jain and Leong use a similar approach to the one taken in this research.

Their intent was to evaluate the supply chain under increased stress due to increased demand. Furthermore, Kelepouris et al. (2005), Ingalls and Foote (2003), Ingalls et al. (2005), and Truong and Azadivar (2005) also used simulation for the analysis of supply chains. These researchers used simulation to create and simulate the dynamics of the supply chains, create different scenarios (inventory policies and forecasting techniques), input real data to the model, and record output data for analysis.

3.4 Supply Chain Analysis

Like in this research, many other studies have used a simple two-stage supply chain. Some of these include: Chen et al. (2000a), Chen et al. (2000b), Gavirneni (2002), Ingalls et al. (2005), Kelepouris et al. (2005), Hasama and Song (2007) and Duc et al. (2008). These studies investigate different areas of the supply chain such as forecasting, lead time, bullwhip effect, information sharing and their impact, one difference between this work and the ones mentioned above is that it considers multiple customers.

Chen et al. (2000a), Chen et al. (2000b), Ingalls and Foote (2003) and Ingalls et al. (2005) studied the effect of demand forecasting in supply chains. They concluded that the way in which forecasts are revised play an important role in supply chains. Chen et al. (2000a) concluded that demand forecasts that are not recalculated for every small change in demand results in lower variability. The more specific research of Chen et al. (2000b) focused on the analysis of the exponential smoothing forecast technique, concluding that forecasts that are constantly updated result in more variability, compared to demand forecasts that are updated only when the incoming demand exceeds established lower and upper levels. The work performed here differs from both Chen et al. (2000a) and Chen et

al. (2000b) because they use correlated demands to analyze their system but this research considered independent constant demand.

Ingalls et al. (2005) describes an algorithm and forecasting technique known as control-based forecasting which is based on statistical control. The control-based forecasting technique is different from other forecasting techniques because it does not update the forecast unless there is proof that incoming demand has exceeded the standard statistical mean. This technique is argued to increase forecast accuracy. The drawback of the control-based forecasting technique studied is that it is not a common practice in industry.

Warburton (2004) moved away from simulation and studied the equations that describe the supply chain in order to better analyze the supply chain and its dynamics. The study was based on mathematical relationships rather than simulation and variability was not introduced in the system. Warburton (2004) calculated solutions to the supply chain equations in order to develop optimal ordering policies to reduce the bullwhip effect and improve inventory management.

The researchers mentioned above have used either mathematical equations to understand the dynamics of supply chains or simulation tools. The body of research mentioned in this section has contributed in the design of the supply chain as well as giving additional information on environmental emissions, supply chains, and simulation, but no research was found to study the relation between demand variability of two tier supply chains and carbon dioxide emissions. This study intends to fill that gap.

4. SCOPE AND METHODOLOGY

The objective of this research is to model the impact of demand variability on the emission of carbon dioxide in supply chains. A supply chain has many transportation modes, global locations, stakeholders, product lines and markets. A complete supply chain with all these factors would be too large and complex to analyze. For this reason, this work focuses on the analysis of a two-stage supply chain. A simulation model was built relying on data from a beverage wholesaler in Rochester, N.Y. to represent the system and the interaction between the echelons (see Appendix A). To further understand the dynamics of the system the model was run under different conditions, thus flexing the system.

4.1 Supply Chain Overview

The simulation model describes a two-stage supply chain in the beverage industry. The main focus is on the distribution system and dynamics of the echelons, the wholesaler and the retailers. The first echelon in the supply chain is the supplier, which sends product to the wholesaler every week. The wholesaler consolidates large quantities of products to later distribute in small quantities to retailers. The product is delivered by a fleet of trucks that is managed by the wholesaler (Figure 1).

In this specific study, a route consists of a group of retailers located in the same area; all retailers in the route are serviced the same day. In this model a wholesaler distributes product to the routes every week by truck. At the same time in which the product is delivered, the order for the next week is received by the truck driver. At the end of each week the wholesaler uses the sum of all route demands to calculate a forecast

of future demand. Consequently, under this scenario the wholesaler checks its inventory level every week and places an order to the supplier. In the same way, orders placed to the supplier are delivered to the wholesaler the following week.

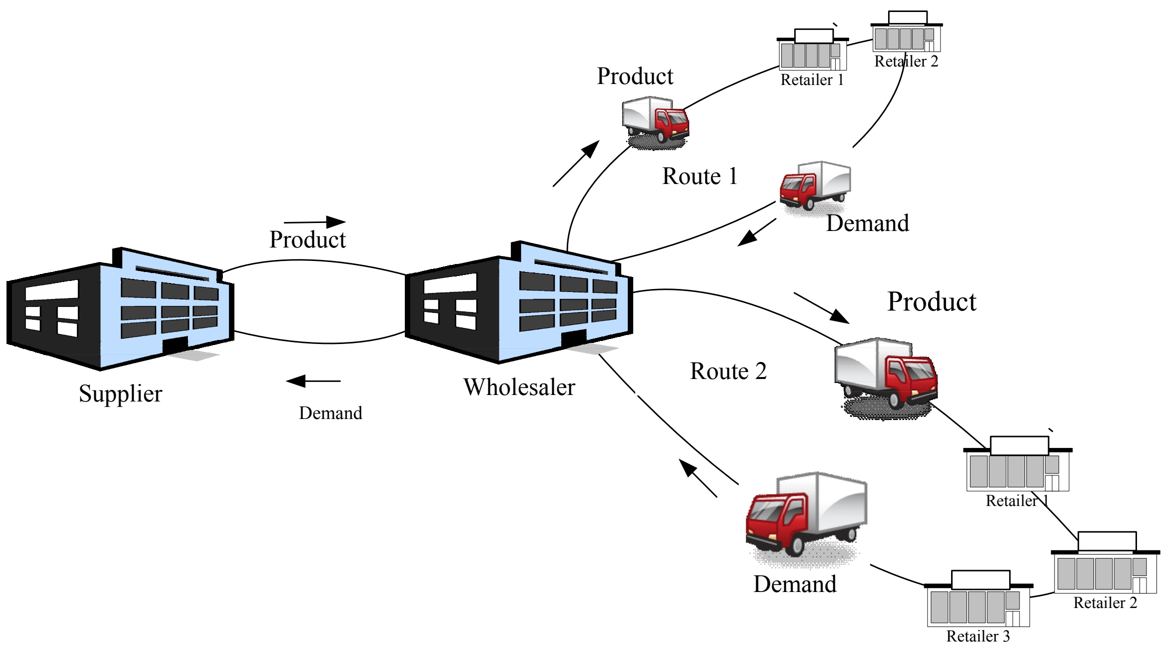

Figure 1. Food and Beverage Supply Chain

4.2 Supply Chain Design

To further illustrate the dynamics of the system, the following section explains the different areas of the supply chain and the variables used to characterize the system. The explanation is divided into logical sections which are the distribution system, routes, route demand, forecasting technique, inventory policy, carbon dioxide emissions, cost, and service level. Furthermore the calculation of the response variables are explained, these are carbon dioxide emissions, cost and service level. Table 1 shows the notations that will be used in the following sections.

Table 1. Model Variables

Route Number Index	**j = (1,2,…N)**	
Total number of routes	N	# of routes
Total number of routes serviced	R	# of routes
Average Demand of Route j	$\bar{Q}_j$	# of cases
Demand of Route j at time t	Q_{jt}	# of cases
Distance of Route j	D_j	miles
Number of Stops of Route j	N_j	# of stops
Time to complete Route j	M_j	min
Truck type Index	**i = (1,2,3)**	
Total Number of Trucks	T	# of trucks
Number of Trucks type i	T_i	# of trucks
Fuel Efficiency of Truck type i	E_i	mpg.
Capacity of Truck type i	V_i	cubes
Capacity of Truck type i servicing route j	V_{ij}	cubes
Days of the week	**k = (1,2,3,4,5)**	
Cost of a Gallon of Diesel	G	$
Regular Labor Wage per Hour	H	$
Overtime Labor Wage per Hour	O	$
Trips made by truck type i to route j in day k	X_{ijk}	# of trips
Week Demand in time t	W_t	# of cases
Demand Forecast in time t	F_t	# of cases
Inventory Level in time t	I_t	# of cases
Order up to Level in time t	S_t	# of cases
Safety Stock	SI	%
Order placed to Supplier at time t	q_t	# of cases
Number of deliveries that required a single trip	A	

4.2.1 Distribution system

The wholesaler uses a truck fleet of size T, for the distribution of their product across a number of routes N. The fleet is composed of different truck types i with different capacities, so that T_i represents the number of trucks of type i. The attributes

used for each truck are loading capacity V_i and fuel efficiency E_i. The volume of the trucks is measured in cubes; which represents the space that one average unit of product occupies. Based on the information obtained from the warehousing department of the local beverage wholesaler, the approximate dimensions of a cube are 15.75 inches of length, 10.62 inches of width and 4.87 inches of height. Fuel efficiency represents the number of miles traveled by the truck with one gallon of diesel.

Real data from the local beverage wholesaler was used to determine the total number of trucks and the percentage of each truck type i that make up the total truck fleet of the wholesaler in the model. For this specific scenario, the same percentage of each truck type i as the local wholesaler data was used. The number of each truck type 1, 2, and 3 for a total number of trucks of 10 is 6, 2, and 2 respectively. The values for the different truck types and their attributes are shown in Table 2.

Table 2. Truck Distribution

	Truck type i		
	i = 1	i = 2	i = 3
T_i	6	2	2
E_i	8 mpg	6 mpg	4 mpg
V_i	1000 cubes	1350 cubes	1650 cubes

4.2.2 Routes

Typically, in order to efficiently service its retailers, the wholesaler separates retailers into routes. Each route has a fixed day k in which it will be serviced. It is assumed that the wholesaler distributes product 5 days a week and that every route is visited only once a week. For this specific case, routes are composed of groups of ten retailers that are located close to each other. The number of routes serviced each day is

determined by the total number of routes N and the total working days in the week, so that every day the wholesaler distributes to N/5 routes, rounded up to the next integer.

The system configuration of the supply chain is here defined by the number of routes N being serviced and the number of trucks T used to distribute the product to the retailers. The configuration of the system is a variable factor used to manipulate the size of the supply chain and it has two levels. The low level mimics the system configuration of the local beverage wholesaler with a similar number of trucks and routes and the high level represents a system five times bigger than the low level system configuration (see Table 3). Two levels were used in order to test if the average carbon dioxide emissions per route would increase as the size of the system increases and also to determine if the findings of this research would apply for different system configurations.

Table 3. System Configuration Levels

Level	System Configuration	
	Truck Fleet	Routes
0	10	50
1	20	100

Route demands are received by the wholesaler and then organized in descending order based on their value. When scheduling the orders in a day, it is assumed for the purpose of this research that the route with the biggest route demand Q_{jt} will be delivered by the truck with the biggest loading capacity V_i available. To determine the amount of time required to complete the route it is important to consider route distance and number of stops in a route. When more than one trip is required it is important to consider the

average amount of time per stop to obtain an accurate delivery time. In order to calculate the values for these two variables the data from the local beverage wholesaler's distribution system was analyzed using linear regression. Equation 1 shows the linear regression resulting from the data analyzed, the R^2 was 0.84.

$$\mathrm{y} = 1.74 * x_1 + 11.92 * x_2 + 157.37 \tag{1}$$

where y represents the dependent value for "route time" and x_1 and x_2 represent the independent values of "distance" and "number of stops" respectively. Using this equation it is assumed that every stop takes an average of 11.92 minutes and that every mile traveled represents a time of 1.74 minutes, which equals an average truck speed of 35 miles/hour. The intercept (157.37 minutes) can be explained as additional activities like lunch hour, fuel loading and maintenance. This research does not consider the intercept because it is assumed that fueling and maintenance are done prior to the time assigned for product delivery. In the same way the time dedicated for lunch will not be considered because it is assumed that it is not part of the 8-hour work day. Based on the previous information the equation used in this study to determine the time required to service a route for a single trip in minutes is shown in equation 2.

$$M_j = 1.74 * D_j + 11.92 * N_j \tag{2}$$

where M_j is the time required to deliver the product for a route j, D_j represents distance of the route j and N_j represents the number of stops in a route j. Equation 2 is

important when more than one trip is required to deliver the route's total demand. Under this scenario the time required for each trip will depend on the number of retailers each truck will deliver product to in the same route as well as the distance of the route.

Route distance, D_j varies from route to route and system to system; in order to emulate the conditions of this supply chain actual route distances were obtained from the local beverage wholesaler and 65 data points were used as sample. The analysis on route distance was made using Arena's Input Analyzer software. To determine the distribution that best fits the data the Chi Square and Kolmogorov-Smirnov tests were used. Two tests were used to have a higher certainty about the quality of the fit. The analysis yielded no standard distribution that generated acceptable p-values (higher than 0.15) for both procedures. When the data were graphed it could be observed that the graph was divided in two separate graphs or clusters, based on this observation the data was separated and analyzed individually resulting into two separate distributions referred as short and long routes (see Figure 2 and Figure 3). The distribution that represented the data better, based on their p-values, was the triangular distribution. The p-values for the tests Chi Square and Kolmogorov-Smirnov for the short routes were 0.224 and 0.150 and for the long routes 0.196 and 0.150 respectively. Short routes represent approximately 50% of the routes and long routes represent the remaining 50%. The triangular distributions used are as follows. The units are in miles.

Short route distribution = Triangular (22.0, 34.2, 72.0)

Long route distribution = Triangular (80.0, 90.2, 155.0)

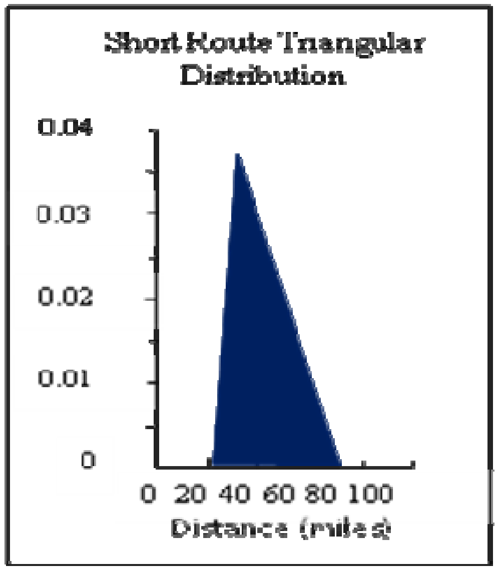

Figure 2. Short Route Triangular Distribution

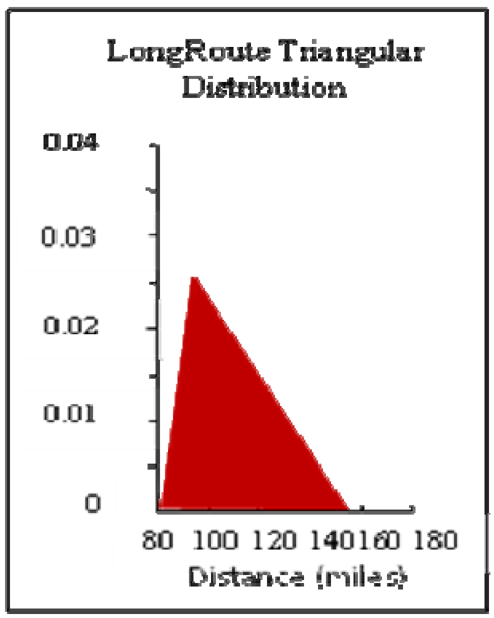

Figure 3. Long Route Triangular Distribution

Short routes range from 22 miles to 72 miles and long routes range from 80 miles to 155 miles. The distance assigned to each route is constant throughout all the experiments. It is assumed that the total distance between all the retailers in a route is

approximately the same among all the different routes. It is also assumed that the distance between retailers is included in the total route distance $D_{j.}$

4.2.3 Route Demand

Route demand represents the sum of the demands from all the retailers in one route. To represent the demand of route j at time t, Q_{jt}, seen by the wholesaler the first distribution considered was the normal distribution. The normal distribution is commonly used in the literature to represent customer demand (Strijbosch and Moors 2003). To test the system under different demand variability, the changing factor coefficient of variation (CV) was used. The coefficient of variation represents the ratio between the standard deviation and the mean of the demand (see Equation 3). With a fixed mean value, the higher the coefficient of variation the higher the standard deviation of Q_{jt}.

$$\text{Coefficient of Variation} = \frac{\sigma}{\mu} \tag{3}$$

With a normal distribution, demand variance can be easily managed by changing the value of the standard deviation represented by σ. Equation 4 shows the normal distribution for the demand of route j in time t.

$$Q_{jt} \sim N\left(\bar{Q}_j, \sigma^2\right) \tag{4}$$

where $\bar{Q}_j$ is the fixed average demand for route j. When the normal distribution was tested under high levels of variance (e. g. CV=80%) it resulted in unrealistic negative demand values as shown in Figure 4. For this reason it was decided not to use a normal

distribution to represent route demand. A triangular distribution was used to better depict the values of customer demand (see Equation 5).

$$Q_{jt} \sim Tria\left(a, mode, b\right) \tag{5}$$

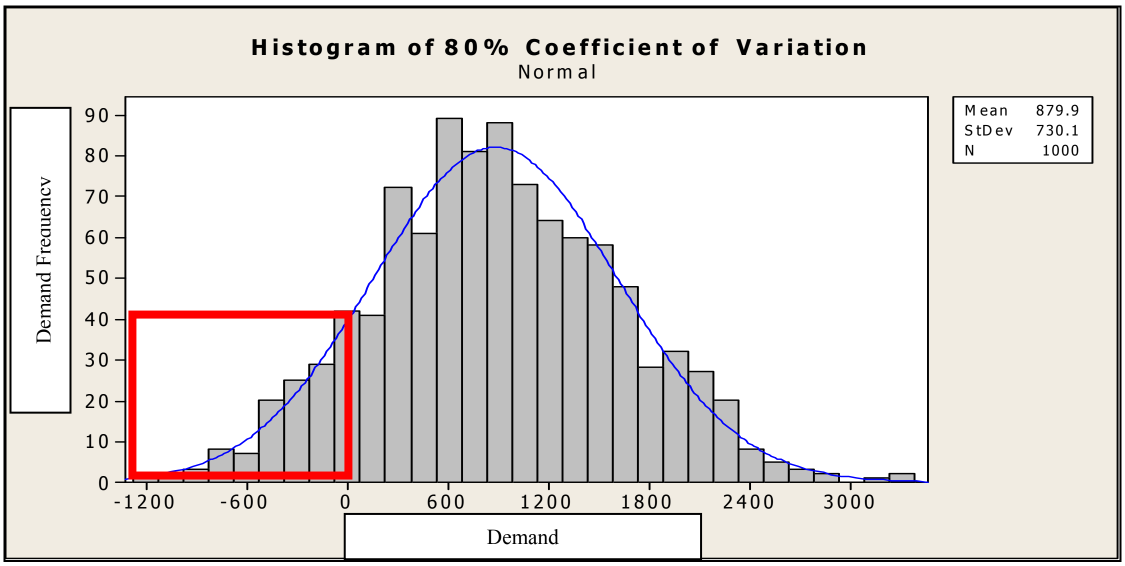

Figure 4. Normal Distribution with 80% Coefficient of Variation

The coefficient of variation is a changing factor used in this study to flex the system under different demand variability. When the coefficient of variation increases it also increases the standard deviation of the demand distribution resulting in bigger swings in demand seen by the customer. Contrary to the normal distribution the standard deviation in a triangular distribution is a calculated from the values a, mode and b of the distribution (see Equation 6).

$$\sigma = \sqrt{\frac{a^2 + b^2 + c^2 - ab - ac - bc}{18}} \tag{6}$$

Several values of the coefficient of variation were studied so that significant variability was introduced in the system. A model was created to understand what variance level flexes the system without going over the time constraints of a day. The result of the test showed that a coefficient of variation of 10% did not show any impact in the efficiency of the supply chain and represented a low level of variability. On the other hand, a coefficient of variation of 70% resulted in demands that required more than one trip to deliver the product. When the coefficient of variation was higher than 70% some demands required four trips to deliver the product, which can result in unrealistic delivery times. Based on these results the low, medium and high levels of the factor coefficient of variation were determined. To represent the levels of the coefficient of variation the values of the triangular distribution were established. Table 4 shows the levels of CV and the respective triangular distribution. To better illustrate the triangular distributions used to represent and manipulate demand variability, Table 5 shows an example in which the value for Q_{jt} is equal to 1,000. Furthermore, the distributions are graphed in Figure 5 so that the spread can be easily observed.

Table 4. Coefficient of Variation and Demand Distribution

Level	CV	Triangular Distribution
0	10%	TRIA ($0.75*Q_{jt}$, Q_{jt}, $1.25*Q_{jt}$)
1	40%	TRIA (0, Q_{jt}, $2*Q_{jt}$)
2	70%	TRIA (0, 0, $3*Q_{jt}$)

Table 5. Example of Coefficient of Variation with Qjt = 1000

Level	CV	Triangular Distribution
0	10%	TRIA (750, 1000, 1250)
1	40%	TRIA (0, 1000, 2000)
2	70%	TRIA (0, 0, 3000)

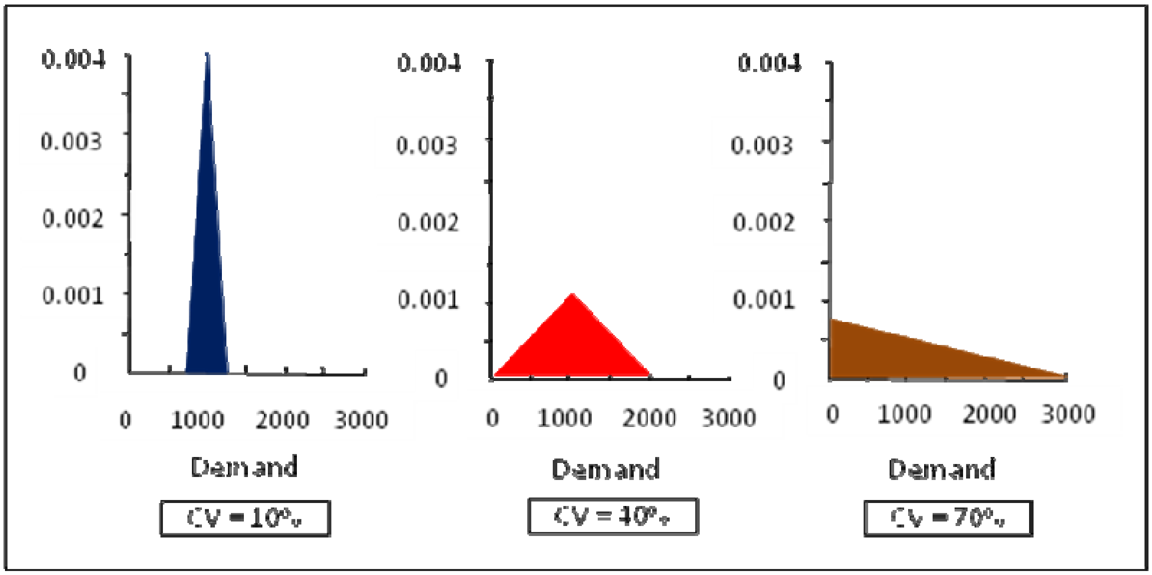

Figure 5. Coefficient of Variation on Triangular Distribution (Q_{jt} = 1000)

In the same way in which the coefficient of variation is used to expose the system to different stress levels, different demand levels are also used to flex the model. The low and high levels of average route demand, $\bar{Q}_j$, were set in order to analyze how the system reacts under different demand levels. The first step is to calculate the demand level that represents the system at its maximum capacity (100 %). The capacity of the system is represented by the sum of the total loading capacity of all the trucks that compose the truck fleet. Weekly total truck loading capacity is determined by the sum of the individual truck loading capacities V_i of the truck fleet multiplied by the number of days in a week (see Equation 7).

$$\text{Weekly total truck capacity} = \left(\sum_{i=1}^{3} \left[T_i * V_i \right] \right) * 5 \tag{7}$$

This study assumes that the weekly total truck loading capacity represents the sum of all the demands from the routes, assuming 100% capacity utilization. The variable Capacity Ratio (CR) was used to flex the system under different demand levels. So when the sum of all the mean route demands is equal to the weekly total truck loading capacity, the system is assumed to be at 100% capacity ratio. In the same way, to determine the individual average route demand $\bar{Q}_j$ the loading capacity of the truck assigned to that route is multiplied by the capacity ratio (see Equation 8). So if the capacity ratio changes, the demand level of system also changes.

$$\bar{Q}_j = V_{ij} * CR \tag{8}$$

where CR is the capacity ratio and $0 < CR < 1$. The capacity ratio was changed to test the system under low, medium and high demand with respect to the system's capacity. The levels of the capacity ratio determined can be observed in Table 6.

Table 6. Capacity Ratio Levels

Level	CR
0	50%
1	70%
2	90%

The base line of 50% CR tests the system at relaxed conditions. At this level, experiments showed that in the majority of the cases only one trip was required to

distribute the product and the responses carbon dioxide emissions, cost and service level almost did not change with changes in demand variability. On the other hand, a CR of 90% takes the system close to the maximum truck capacity in which more trips are required to deliver the product and the responses change greatly in relation to demand variability. To better understand the behavior of the system from low to high demand, a middle point of 70% was also used in the analysis.

4.2.4 Forecasting Technique

Typically a wholesaler uses a forecast to predict future demand. The forecast is later used to calculate the amount of product to order from the supplier. The exponential smoothing forecasting method has been used in previous studies that analyze supply chains (Chen et al. 2000a, Kelepouris et al. 2005, and Ingalls et al. 2005). Equation 9 shows the forecast at time t, F_t, using the exponential smoothing technique in the form of:

$$F_t = (W_{t-1} * \rho) + (1-\rho) * F_{t-1} \tag{9}$$

where, ρ is the smoothing constant, F_{t-1} is the forecast of the previous period t and W_{t-1} represents the week demand of the previous period t. The larger the smoothing constant value, the larger the weight given to the previous demand W_{t-1}. Similarly, the lower the smoothing constant value, the more weight is given to the previous forecast F_{t-1}. This study considered different levels for the smoothing constant (see Table 7). The equally spaced levels were chosen to study the impact of the different forecast configuration. The low level of the smoothing constant was set to 0.2 in order to

understand how the system would behave when more weight is given to the previous forecast. To understand the opposite case, the high level of the smoothing constant was set to 0.8 in which more weight is given to the previous route demand, adjusting better to fluctuations in demand. The medium level was set to be 0.5, which gives the same importance to the previous forecast and previous route demand.

Table 7. Smoothing Constant Levels

Level	ρ
0	0.20
1	0.50
2	0.80

4.2.5 Inventory Policy

Route demands received by the wholesaler are deducted from the inventory prior to the delivery of product to the retailers. The sum of the demands of all routes j in any period t represents the total week demand W_t (see Equation 10).

$$W_t = \sum_{j=1}^{N} Q_{jt} \tag{10}$$

This demand is subtracted from the inventory and the previous order placed to the supplier (see Equation 11). At the end of the week, the previous order placed by the wholesaler to the supplier is received by the wholesaler, so that the inventory level has the form of:

$$I_t = I_{t-1} + q_{t-1} - W_t \tag{11}$$

At the end of the week the inventory level is revised and if required, an order is placed to the supplier. It is assumed that the wholesaler uses an order-up-to level inventory policy. At the end of period *t*, the wholesaler places an order quantity q_t (see Equation 12).

$$q_t = S_t - S_{t-1} + W_{t-1} \tag{12}$$

There is a fixed lead time for the order placed to the supplier; the lead time assumed in this study is one week. In order to determine the order-up-to level, S_t, the wholesaler calculates a demand forecast based on the previous demand forecast using the exponential smoothing forecast explained in section 4.2.4. Using the new forecast, the order-up-to level is then calculated (see Equation 13).

$$S_t = F_t * (1 + SI) \tag{13}$$

where SI represent the safety factor. For this study a safety factor SI of 30% of the demand forecast was used. Considering that the safety factor was established for a low level of demand variability, defined in this study by a coefficient of variation of 10% (so that the standard deviation is 10% of the total route demand), the safety factor was setup to be three times the standard deviation of the demand. With a safety factor of 30%, it is expected that the wholesaler will have enough inventory to fulfill the demand for a low level of variability. The value for safety inventory is fixed throughout the simulation and its impact will not affect the comparison between the different scenarios under which the system will be run.

4.2.6 Carbon Dioxide Emissions

To measure carbon dioxide emissions produced during product distribution, it was assumed that 10.1 kilograms of carbon dioxide is produced for every gallon of diesel consumed. The loading capacity of the different trucks is correlated to the engine power measured in horse-power required to move the load. Therefore a larger truck typically requires a larger horse-power and presents lower fuel efficiency in relation to a smaller truck. Truck type, route distance and number of trips are values required to calculate the total carbon dioxide emissions produced. It is assumed that when the truck is idle unloading the product at the retailer, the engine is turned off and no carbon dioxide is produced. The following formula depicts how to calculate weekly carbon dioxide emissions. In the equations below, X_{ijk} represents the number of trips made by truck i for route j during day k (see Equation 14).

$$\text{Carbon Dioxide Emissions} = \left[\sum_{k=1}^{5} \sum_{j=1}^{N} \sum_{i=1}^{T} \left[\frac{X_{ijk} * D_j}{E_i} \right] \right] * 10.1\, kg/gal. \qquad (14)$$

The method used to calculate the carbon dioxide content in a gallon of conventional diesel was the "EPA's Emission Facts" that is intended as a reference for estimating emissions (EPA 2005). The departing point for the calculation is the diesel carbon content per gallon of diesel, which the conventional average value is 2,778 C grams/ gallon. In order to account for the percentage of fuel not oxidized, the molecular weight has to be multiplied by the oxidation factor. Based on the same reference, the oxidation value for oil products used is 99 percent. The final step is to consider the

molecular ratio between the molecular weight of carbon dioxide (m.w. 44) and the molecular weight of carbon (m.w. 12). The equation to calculate the carbon dioxide emissions of gallon of diesel is as follows.

$$CO_2 / Gallon\ \ of\ \ Diesel = Carbon\ content / gal * Oxidation\ factor * \frac{Molecular\ weight\ CO_2}{Molecular\ weight\ C} \quad (15)$$

If values are substituted then,

$$CO_2\ /\ Gallon\ \ of\ \ Diesel = 2{,}778\,C\ g\ /\ gal * 0.99 * \frac{44}{12}\ =\ 10{,}084\ g = 10.1\ kg\ /\ gal$$

4.2.7 Cost

The cost is calculated based on the hours needed for the distribution of the product as well as the gallons of diesel consumed by the delivery trucks. The values for labor and fuel cost are described in Table 8. The Bureau of Transportation Statistics shows an average hourly rate for truck drivers of $ 15.75; based on this information an hourly rate of $16 was chosen (US Department of Commerce 2004). Overtime labor wages consists of 50% increase over the regular labor wages.

Table 8. Labor wages and Fuel Cost

Regular labor wages per hour	$16.00
Overtime labor wages per hour	$24.00
Cost of one diesel gallon	$4.50

To calculate the weekly cost associated with labor, the time required to deliver the product to the retailers M_j was used. Total labor cost is the sum of regular labor cost and overtime labor cost. In respect to the cost of fuel, distance of the route D_j and fuel

efficiency of truck E_i are used to calculate the consumption of diesel. In the equations below, X_{ijk} represents the number of trips made by truck i for route j during day k.

$$\text{Diesel Cost} = \left[\sum_{k=1}^{5} \sum_{j=1}^{N} \sum_{i=1}^{T} \left[\frac{X_{ijk} \ * \ D_j}{E_i} \right] \right] * G \tag{16}$$

$$\text{Regular Labor Cost} = \left[\sum_{k=1}^{5} \sum_{j=1}^{N} \sum_{i=1}^{T} \left[X_{ijk} \ * \left(\frac{M_j}{60} \right) \right] \right] * H \tag{17}$$

$$\text{Overtime Labor Cost} = \left[\sum_{k=1}^{5} \sum_{j=1}^{N} \sum_{i=1}^{T} \left[\left(X_{ijk} \ * \left(\frac{M_j}{60} \right) \right) - 8 \right] \right] * O \tag{18}$$

s.t.

$$\sum_{j=1}^{N} X_{ijk} * \left(\frac{M_j}{60} \right) \ \rangle \ 8 \qquad \forall \, i, k$$

$$\text{Total Labor Cost} = \text{Regular Labor Cost} + \text{Overtime Labor Cost} \tag{19}$$

4.2.8 Service Level

When analyzing a supply chain it is important to also consider factors that measure the performance of the system like service level. In this study the following situations are considered to be detractors from service level:

1. When the wholesaler does not have enough product in inventory to immediately fulfill an order placed by the retailers in a route.

2. When more than one trip is required in order to deliver product to the retailers in a route. More than one trip is required when the demand from the route exceeds the loading capacity of the truck.

In this way, service level is defined in this research as the ratio between the instances in which only one trip was required to deliver product to a serviced route and the total number of routes serviced. Deliveries that require a single trip for the complete delivery of the product are represented by A and total number of routes serviced is represented by R. Then, service level is calculated by,

$$\text{Service Level} = \frac{\text{Number of deliveries that required a single trip}}{\text{Total number of routes serviced}} = \frac{A}{R} \tag{20}$$

4.3 Simulation Model

A simulation model was created to simulate the dynamics of the supply chain (see Appendix B). The simulation model can be separated into sections that interact together. The sections "truck creation" and "route creation" happen only at the beginning of the simulation. After routes have been created they move to the "demand assignment" and "route separation" sections. The sections "route and truck assignment" and "order management" are responsible for the main calculations in the model. The "wholesaler" section is divided into sub-sections and manages the forecast and ordering of product to the supplier. Finally, the section that controls the timing of the simulation is "route control" that is connected with the "termination condition" section that ends the simulation model. Figure 6 explains in a graphical form the connections and relations between sections. Dashed returning lines represent entities in a weekly cycle.

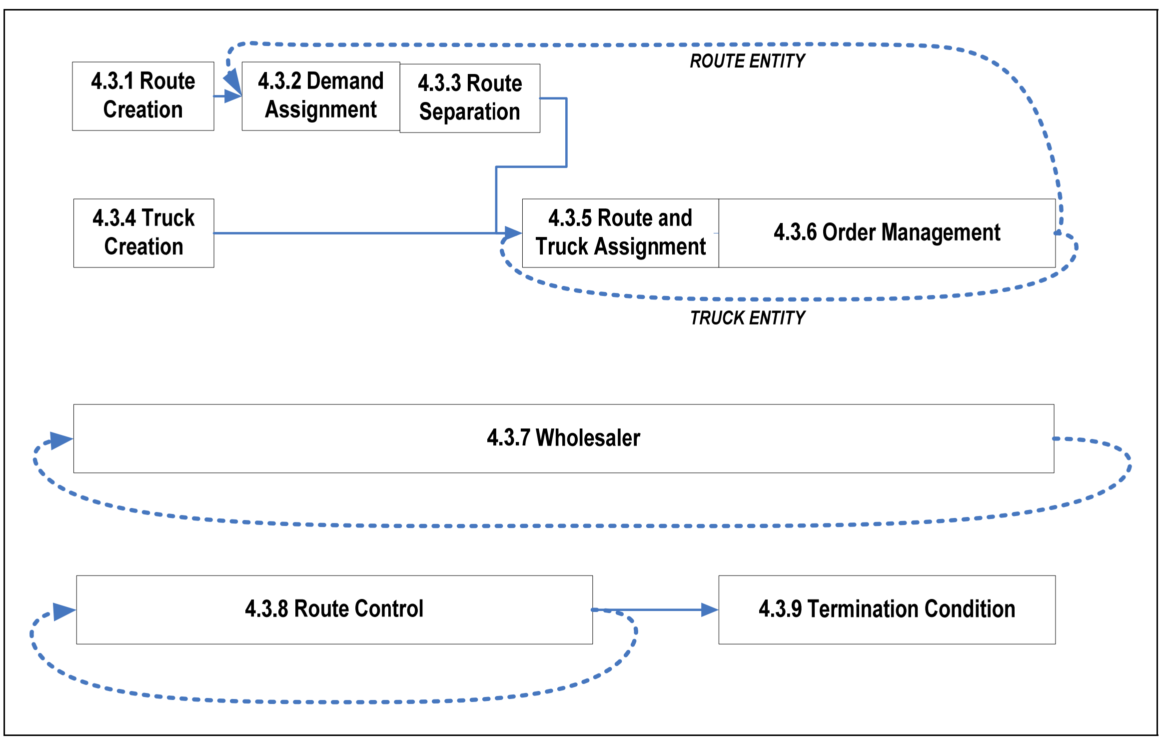

Figure 6. Simulation Diagram

4.3.1 Route Creation

The "route creation" section initiates the simulation model creating the routes (see Figure 7). The number of routes created is equal to the value of the variable "Total Num Routes" which represents the total number of routes. After the routes are created they move into the "Initialize Values" Assign module in which the attribute "route number" is assigned. Additionally the fixed attributes of "average demand" ($\bar{Q}_j$) and "delivery day" (k) are assigned. The factor Capacity Ratio is used to determine the average demand. Values are assigned using a two dimensional array named RouteData() that was previously created and contains data of the routes' delivery day, maximum average demand, route distance and number of stops. Another global variable that is created is "initial demand" that represents the sum of all the individual "average demand" of the routes created. It is used for the initialization of the system in section 4.3.7. Routes are then sent to demand assignment and route separation.

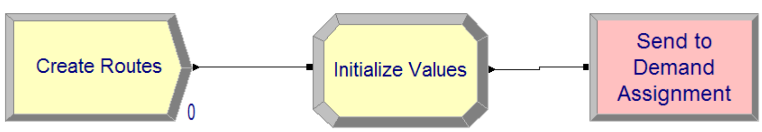

Figure 7. Route Creation and Initialization.

4.3.2 Demand Assignment

The next section is "demand assignment," even though this is not the logical next step in the process, within a simulation environment that is not a factor that influences the outcome of the simulation. Routes are received from the "route creation" section through the "Assign Demand" Station. The demand value will depend on the variance level determined. To assign the correct variance level a Decide module "DOE Demand

Variability Factor" with three exit points is used, each exit is connected to an Assign module that calculates the demand at the three variance levels (see Figure 8). The Decide module evaluates the value of the global variable "DOE Variance," which determines the exit point of the route. The "DOE Variance" value is changed based on the scenario being run. The demand formula follows a triangular distribution, as explained in section 4.2.3 of the methodology.

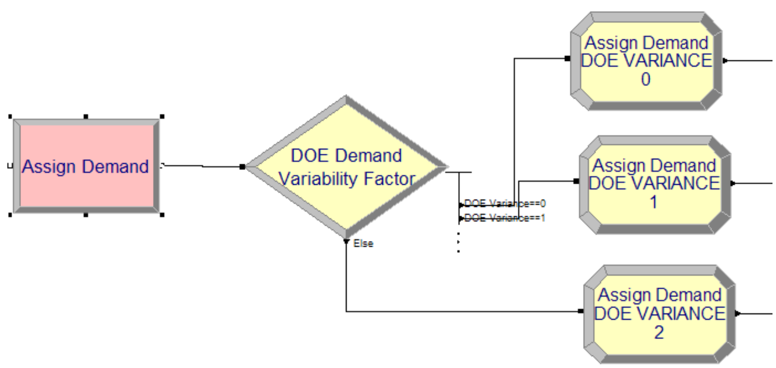

Figure 8. Demand Assignment

4.3.3 Route Separation

After route demand has been calculated the routes are separated by "delivery day" to later be serviced by the wholesaler during the week (see Figure 9). All routes move into a Decide module called "Sent to Day Hold" where the attribute "delivery day" is evaluated. The Decide module has five exit points that connect to Hold modules "Hold Monday," "Hold Tuesday," "Hold Wednesday," "Hold Thursday," "Hold Friday" that are used to represent days. For example, routes with a delivery day k = 1 move to a Hold module representing the day Monday.

Once in the Hold module queue, the entities are arranged in descending order based on their attribute “route demand.” The arrangement was done by setting the queue rule to “Highest Attribute Value.” The routes will stay on hold until they receive a specific signal coming from a Signal module in the “route control” section. When the routes are liberated they move to the retailer as incoming orders with a demand.

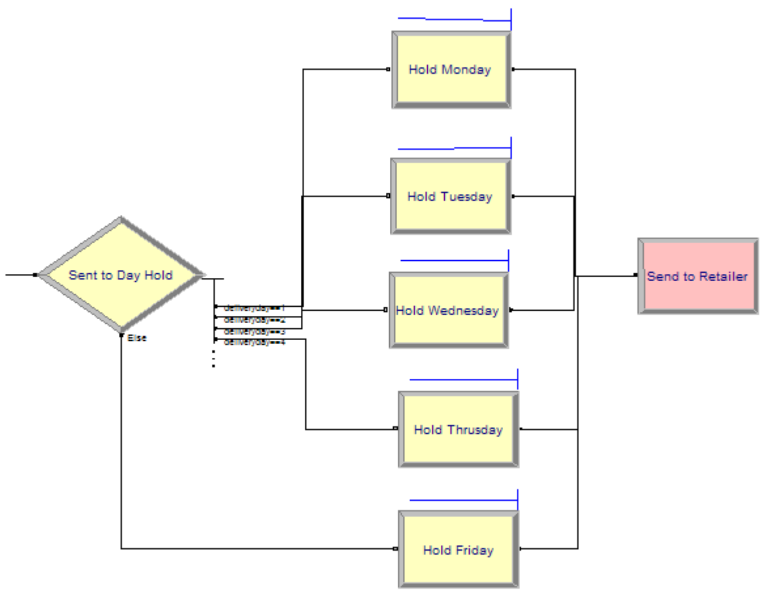

Figure 9. Route Separation by Delivery Day

4.3.4 Truck Creation and Initialization

The creation of trucks is done using a Create Module called “Create Trucks,” different from the one used in section 4.3.1 “route creation.” The truck number to be created is determined by the sum of the total number of trucks of each truck type i. Like the routes, trucks also get assigned an attribute “truck number” using the Assigned module “Assign Truck Number” (see Figure 10). Different truck types i, have different values for the attributes “load capacity” and “fuel efficiency.” To properly assign these

values the “Truck type Separation” Decide module is used to redirect the trucks towards the correct Assign modules (see Figure 10). This is done by evaluating the attribute “truck number” against the variables “Numtruck1000,” “Numtruck1350,” and “Numtruck1650,” that represent the total number of trucks of each type i specified. For example, if the variable “Numtruck1000” is equal to 6, trucks with the attribute “truck number” lower or equal to 6 will be assigned values representing truck type 1.

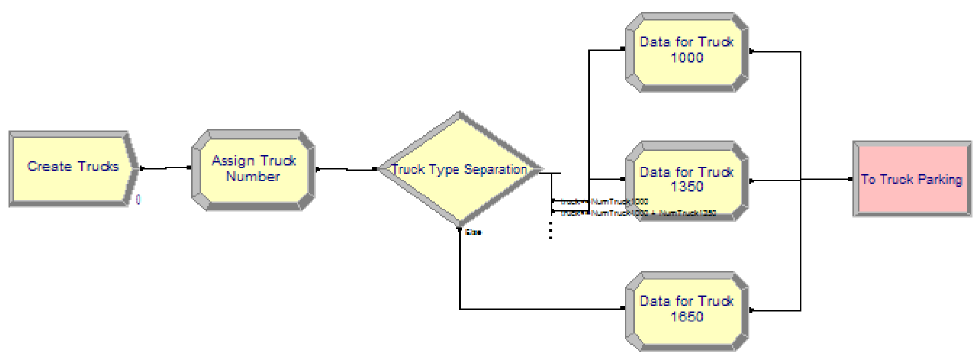

Figure 10. Truck Creation and Initialization

4.3.5 Truck and Route Assignment

After routes and trucks are separated they move into the “truck and route assignment” section. The first entities to enter this section are the truck entities that move to a Hold module called “Hold Truck,” which represents a parking lot for the trucks. Using the queue of the Hold module, trucks are organized in descending order based on the attribute “load capacity.” At this moment both entities are organized in descending order and wait on Hold modules for a signal or condition to be liberated. When liberated, the routes with the highest “route demand” are matched with the trucks with the highest “load capacity.”

Routes are liberated from their day hold with a signal created at the section 4.3.3.8 called "route control." After being liberated, routes arrive to the "truck and route assignment" section entering the "Hold Route" module (see Figure 11). In the same way trucks are liberated from their hold and move into the "Match Trucks" module in which trucks and routes are matched. The arrival of the truck entities to the "Match Trucks" module queue liberates the routes from the hold. Consequently trucks and routes move into a Match module to be united and then into a Batch in which they become one entity that we will refer to as an Order. Now that the route and truck are united into an "order," they proceed to the "response" section.

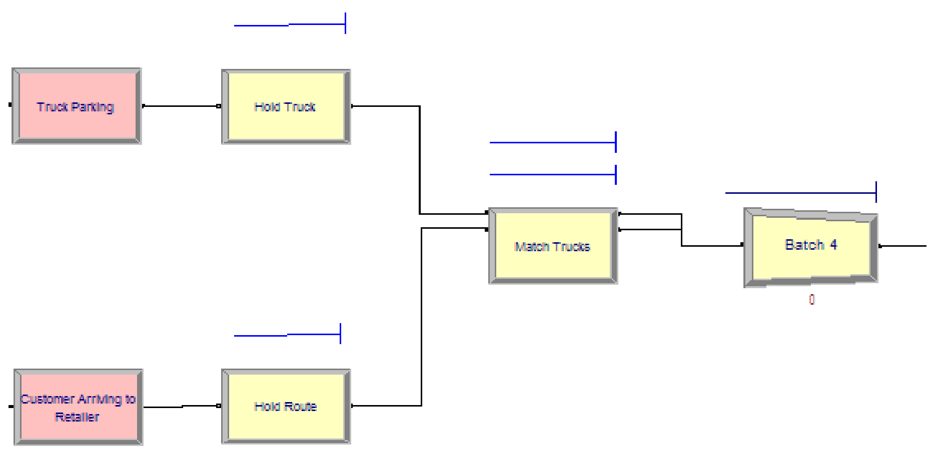

Figure 11. Truck and Route assignment

4.3.6 Order management

"Order management" is the section in which most of the responses are calculated and added into global variables that are later recorded in an Excel file. The "order management" section is divided into several sub-sections. These sub-sections are "order

evaluation," "inventory management," "trips and duration calculation," "response calculation," and "truck and route separation."

4.3.6.1 Order evaluation

"Order evaluation" is intended to error proof "route demand" values that could be assigned when using a triangular distribution with high variance, explained in section 4.2.3. To verify the correct assignment of values the Decide module "Evaluate Route Demand" evaluates the condition of "Route Demand > 0" (see Figure 12). When "route demand" is equal or less than zero, the counter "No Trip" is incremented and the entity is separated so that the truck and route return to their hold modules. If the demand value is positive then the global variable "week demand" is increased by the value of "route demand." "Week demand" is one of the outputs of the model used to calculate the standard deviation of the orders and it represents the total demand in a week. It is also used to calculate the wholesaler order to the supplier.

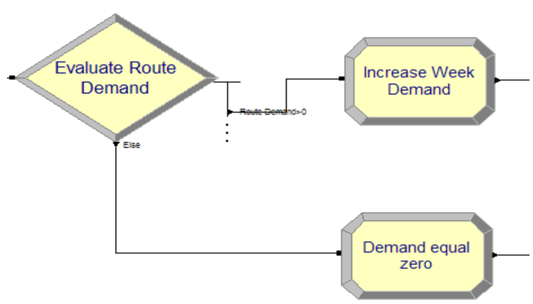

Figure 12. Order Evaluation and Increase Week Demand

4.3.6.2 Inventory Management

To determine if the order will be serviced it is necessary to confirm that the inventory level is greater than the attribute “route demand.” The comparison between the global variable “inventory” and the entities attribute “route demand” is done with the Decide module “Inventory Greater than Demand.” If there is inventory to fulfill the order, the batched entity moves into the Assign module “Reduce Inventory” to simulate the deduction of inventory and loading of the truck with product. If there are not enough products in inventory the order is routed to a different Assign module called “Assigned No Inventory” so that the counter No Inventory is increased. Consequently the entity is separated and the truck and route entity return to their hold modules (see Figure 13).

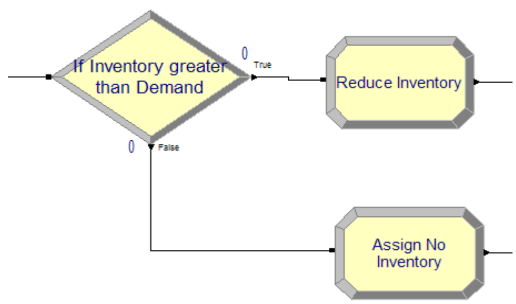

Figure 13. Inventory Management

4.3.6.3 Trips and Duration Calculation

In order to calculate carbon dioxide emissions, cost and service level it is important to first calculate the number of trips required to deliver the product to the routes. In order to do the calculation, the entity enters an Assign module called “Calculate Number of Trips” in which the ratio between route demand and truck capacity is rounded to the next whole number. For example a “route demand” equal to 1300, delivered by a truck with “load capacity” 1000 will result in a ratio of 1.3, when rounded to the next

higher integer the number of trips required is equal to 2. The duration of the delivery will vary depending on the number of trips made by the truck. For this reason the entity enters a Decide module called "If Number of Trips Equal 1" where the attribute "num trips" is evaluated. Each of the four Assign modules connected to the Decide module calculates the duration considering 1, 2, 3 or 4 trips (see Figure 14). The values for route distance and number of stops in route are used to calculate the duration, these values are in the array RouteData(). The formula to calculate the duration of all the trips is as follows,

$$\text{Duration} = ((\text{Route Distance}*1.74)*\text{NumTrips}) + (\text{Route Stops}*11.92) \qquad (21)$$

Routes have a fixed number of stops; the only variable value is the number of trips required for the delivery of product. In addition to calculating "duration" the model also increments a counter to record if the trips required were 1, 2, 3 or 4.

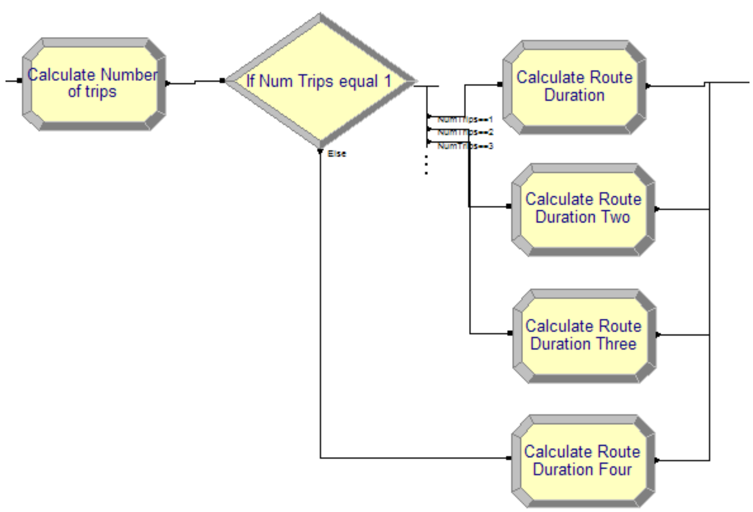

Figure 14. Number of Trips and Delivery Duration

4.3.6.4 Response calculation

The "response calculation" sub-section is one of the most important of the model. The model uses several assigned modules to calculate the responses as well as to add the individual trip responses to global variables. The first Assigned module calculates the number of gallons consumed by the truck considering all the trips required. Equation 22 shows the equation used in the model:

$$\text{Gallons Consumed} = \left(\frac{\text{Route Distance}}{\text{Fuel Efficiency}}\right) * \text{NumTrips} \qquad (22)$$

Gallons consumed is then multiplied by the average amount of carbon dioxide produced per gallon of diesel combusted (10.1 kilograms/gallon), refer to section 3.2.6 for the calculation. Also, using the information for gallons consumed diesel cost is calculated by multiplying it by the cost of a gallon of diesel.

To calculate the labor associated with the delivery, an order enters a Decide module called "If Duration Smaller than 8 Hours" to determine if there will be overtime labor associated (see Figure 15). If the attribute "duration" is smaller than 8 hours then the rate for regular labor hour is used and the information is stored in the global variable "regular labor." On the other hand when the duration of the trips required to deliver the product exceeds 8 hours, the first 8 hours are calculated using the regular labor rate and the remaining hours ((Duration/60) – 8) are calculated at the overtime labor rate. Using another module the variable "regular labor" and "overtime labor" are added to the global variable "total regular labor" and "total overtime labor."

Service level is updated for every order delivered. The equation used for service level considers the total number of orders that requires more than one trip and the instances where there were not enough products in inventory to deliver the product in relation to the total number of routes serviced. Finally the batched entity moves into a Delay module called "Delivery Duration" which delays the entity an amount of time equal to the value of the attribute "duration." The delay simulates the delivery of product including all the trips and stops made by the truck.

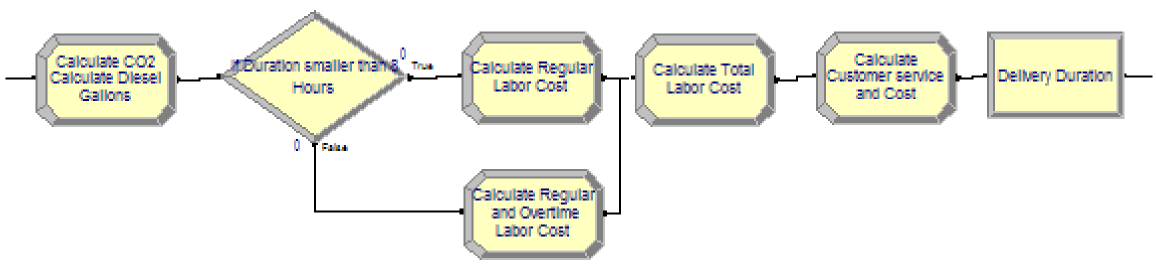

Figure 15. Response Calculations

4.3.6.5 Truck and Route Separation

The final sub-section of the "order management" section is "truck and route separation." After the calculations have been completed, it is necessary to separate the batched entity in order to repeat the cycle for the next week. To do this the order is sent into the Separate module "Separate Truck and Route" to split the entity into truck and route entities. After the entities have been separated they enter a Decide module to return the truck and route entity to their hold the Route Modules "To Day Separation" and "Return to Truck Parking" (see Figure 16).

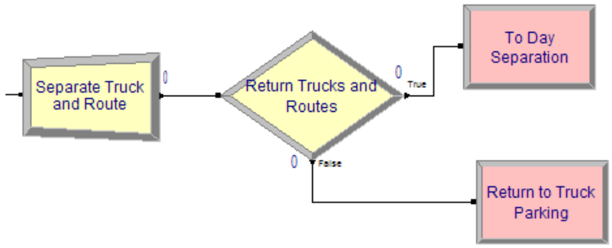

Figure 16. Truck and Route Separation

4.3.7 Wholesaler

The “wholesaler” section is responsible for the initialization of the wholesaler’s inventory, and the repetitive cycle of forecast and ordering. This section is separate from the rest and has its own Create module called “Create Inventory” that creates an entity at the beginning of the simulation (see Figure 17).

4.3.7.1 Wholesaler Initialization

The first sub-section “wholesaler initialization” is used to initialize the variable “previous forecast,” “inventory,” “desired inventory level,” and “previous order.” In this study it is assumed that there is no variability previous to the beginning of the simulation so that the variable “previous forecast” and “previous order” are equal to the total weekly average demand represented by the variable “initial demand.” In the same way the “inventory level” and “desired inventory level” are equal to the variable “initial demand” plus the safety inventory. When the variables are initialized, the entity then moves into a weekly cycle called “forecast and ordering.”

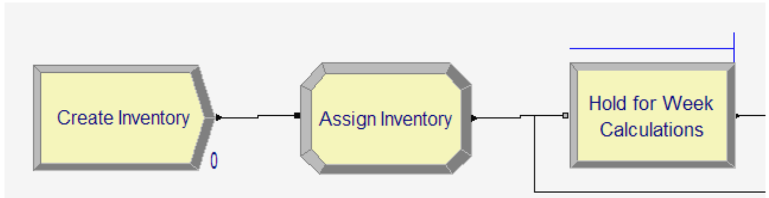

Figure 17. Wholesaler Initialization

4.3.7.2 Forecast and Ordering

The repetitive sub-section, “forecast and ordering,” starts with the Hold module “Hold for Week Calculation” that retains the entity until it is liberated by a signal from the “route control” section. The first step of the cycle is to calculate the demand forecast for the following period. In the same way as the “route demand” the variable “forecast” is also a changing factor in the simulation model. For this reason the model uses a Decide module called “DOE Forecast Factor” that evaluates the global variable “DOE forecast” to redirect the entity based on the scenario being run (see Figure 18). The generic formula for forecast used is:

$$\text{Forecast} = (\text{Week Demand}*\rho) + ((1-\rho)*\text{Previous Forecast}) \qquad (23)$$

Using the “forecast” value, the variables “desired inventory level” and “order” are then calculated. “Desired inventory level” is equal to “forecast” plus a safety factor of 30% used in this study. The variable “order” is just the difference between the global variables “desired inventory level” and “inventory.” When the “inventory” is higher than the “desired inventory level” the value or the order is zero. The next Assign module

"Order Arrival to Inventory" is used to simulate the arrival of product from the supplier to the wholesaler; it is represented by increasing the "inventory" by the variable "previous order." Because the model simulates a weekly cycle, it is important to assign the present values of "forecast" and "order" to "previous forecast" and "previous order," so that it represents the change in time.

To verify the variability of the demand it is important to record the "week demand" and weekly "order" to the supplier, the model uses a Write module named "Write Demand and Order" to export the data to an Excel file. To finish the cycle it is important to reset the variable "week demand" to zero so that it can record the incoming week demand.

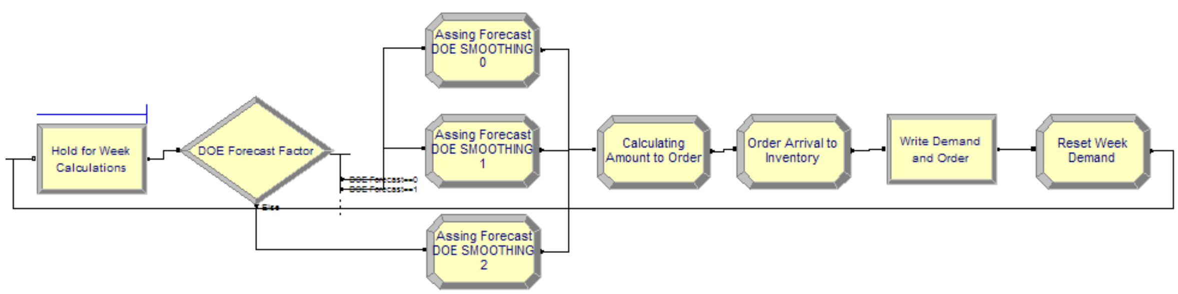

Figure 18. Forecast and Ordering

4.3.8 Route control

The section that controls when to liberate the routes from their daily hold is the "route control" section. It is a repetitive cycle made up of signals and delays that regulate the timing of the system (see Figure 19). Each delay retains the entity for 24 hours after which it enters a Signal module that sends a signal value correlated to a daily Hold of

section 4.3.3. A complete cycle is equal to one week of production based on a total number of day's k.

Additionally, the section is responsible for updating the week number of the simulation. The variable "week number" is of great importance because the data of "week demand" and week "orders" to the retailer is based on the week number. The cycle starts with the Assign module "Create Signal," every time the entity enters the cycle the variable "week number" changes value to "Week Number = Week Number + 1." This variable is also used to determine when the simulation will end.

At the end of the week cycle there is a Signal module called "Week Calculation Signal" that is used to liberate an entity in the "forecast and order" section. To determine if the simulation will continue one more week or if it will move to the termination section, the variable "week number" is evaluated in the Decide module "Write Modules and Finish." The variable is compared to a value that represents the duration in number of weeks of the simulation model.

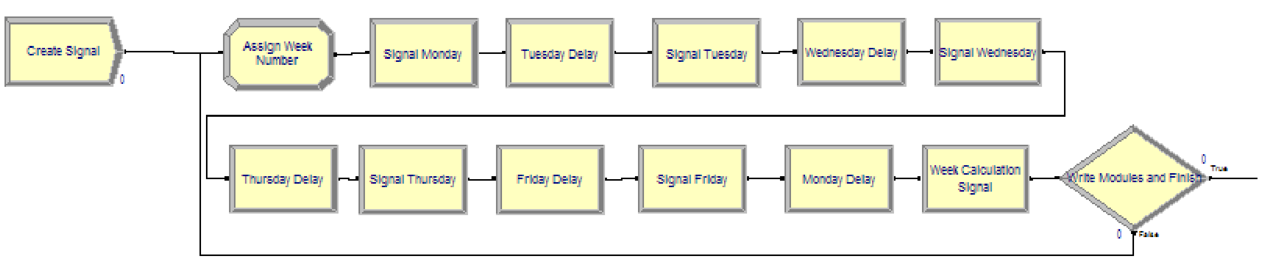

Figure 19. Route Control

4.3.9 Termination Condition

The "termination condition" section is controlled by the counter "week number." This logic allows the extension of the running time of the simulation model by simply

changing a value. When the week number equals the week established as the duration of the simulation the entity moves into the "termination condition" section. Before the simulation ends it is important to write the values for "total carbon dioxide emissions," "total cost," and "customer service level" required to analyze the data of the experiment scenarios. The information is written using the Write module "Write Responses" that export information to an Excel file. In addition to the main responses other variables like "total gallons," "total diesel cost," "total labor cost," "total regular labor," "total overtime labor," "total week order," "one trip," "two trips," "three trips," "four trips," "no inventory," and "no trip" are exported. To finish the simulation the entity enters the Assign module "Terminate Simulation" in which the variable Terminate changes value from 0 to 1, making the termination condition "Termination = 1" true, therefore ending the simulation (see Figure 20).

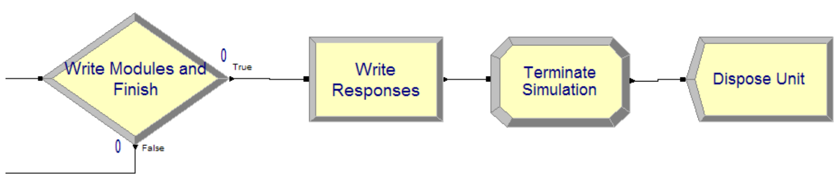

Figure 20. Termination Condition

4.4 Model Assumptions

To better understand the model it is important to consider the assumptions made in this study. These are the assumptions included in the model:

- The average speed of the truck is 35 mph
- The average amount of carbon dioxide per gallon of diesel consumed is 10.1 Kg
- Trucks are turned off when idle unloading product
- Trucks with higher load capacity have a lower fuel economy
- Fuel economy is constant
- Routes are serviced on the same day every week
- All trips to the route to deliver product are done with the same truck
- Every route is serviced once a week
- The cost of regular labor is $16.00 an hour
- The cost of overtime labor is $24.00 an hour
- The cost of a gallon of diesel is $4.50
- Fueling and loading time are considered negligible
- The distance between retailers in a route are normally distributed
- The supplier has unlimited replenishment capacity

4.5 Design of Experiment

The simulation model previously described was used to simulate different scenarios. Several experiments were conducted to analyze the responses carbon dioxide emissions, cost, and service level. The changing factors were system configuration, coefficient of variation, capacity ratio, and smoothing constant.

In the statistical model, the factor system configuration (SC) has two levels, and the factors coefficient of variation (CV), capacity ratio (CR), and smoothing constant (ρ) were considered with three levels. The statistical model considers all the main effects, 2-way interactions, 3-way interactions and 4-way interactions. Table 9 shows the levels of the different factors.

Table 9. Factors and Levels of Experiment

		Level		
Factors		**Low**	**Medium**	**High**
System Configuration	SC	0	-	1
Coefficient of Variation	CV	10%	40%	70%
Capacity Ratio	CR	50%	70%	90%
Smoothing Constant	ρ	0.2	0.5	0.8

The explanation of the factors and their levels can be found in section 4.2.2 for system configuration, section 4.2.3 for coefficient of variation and capacity ratio, and section 4.2.4 for smoothing constant. The main responses recorded were used to determine the impact of the changing factors and are shown in Table 10.

Table 10. Main Responses

Main Responses
Total CO_2 emissions
Total Cost
Service Level

The four factors are used to create a $3^3 * 2^1$ full factorial design to analyze the responses. The experiment has 54 treatment combinations and each treatment combination was replicated 1,000 times. The number of replications allows for responses with a smaller confidence interval. The 54 treatment combinations of the experiment can be observed in Table 11.

Table 11. Coded Treatment Level Combinations (TLC)

TLC	CR	CV	ρ	SC		TLC	CR	CV	ρ	SC
1	0	0	0	0		28	0	0	0	1
2	1	0	0	0		29	1	0	0	1
3	2	0	0	0		30	2	0	0	1
4	0	1	0	0		31	0	1	0	1
5	1	1	0	0		32	1	1	0	1
6	2	1	0	0		33	2	1	0	1
7	0	2	0	0		34	0	2	0	1
8	1	2	0	0		35	1	2	0	1
9	2	2	0	0		36	2	2	0	1
10	0	0	1	0		37	0	0	1	1
11	1	0	1	0		38	1	0	1	1
12	2	0	1	0		39	2	0	1	1
13	0	1	1	0		40	0	1	1	1
14	1	1	1	0		41	1	1	1	1
15	2	1	1	0		42	2	1	1	1
16	0	2	1	0		43	0	2	1	1
17	1	2	1	0		44	1	2	1	1
18	2	2	1	0		45	2	2	1	1
19	0	0	2	0		46	0	0	2	1
20	1	0	2	0		47	1	0	2	1
21	2	0	2	0		48	2	0	2	1
22	0	1	2	0		49	0	1	2	1
23	1	1	2	0		50	1	1	2	1
24	2	1	2	0		51	2	1	2	1
25	0	2	2	0		52	0	2	2	1
26	1	2	2	0		53	1	2	2	1
27	2	2	2	0		54	2	2	2	1

Usually, the run order of the treatment combinations is randomized to eliminate the confounding of effects due to warm up periods, learning curves, and changes in conditions, and other uncontrolled variables. However, with the use of simulation the experiment can be run in any order because it is not affected by external factors. For this reason the experiment was run in the original treatment combination order. The simulation model was run for a period of 13 weeks. The number of weeks used allowed enough time to see the impact of demand variability and analyze the effect on the system. Each treatment combination with 1000 replications took approximately 7 minutes to run, using a Pentium 3 processor.

Secondary responses have also been recorded in order to be used as validation and verification and also to calculate other data that will be used to analyze the main responses, for example to calculate the average number of trips per route; they are shown in Table 12.

Table 12. Secondary Responses

Secondary Responses
Total diesel gallons
Total diesel cost
Total labor cost
Total regular cost
Total overtime cost
Total number of orders
Number of deliveries with one trip
Number of deliveries with two trips
Number of deliveries with three trips
Number of deliveries with four trips
Number of periods with no inventory
Number of periods with no demand

The statistical analysis was done using the statistical software Minitab 14 ®. The results and analysis section uses ANOVA tables for every response as well as main effect plots, interaction plots and regressions to draw conclusions from the data.

5. RESULTS AND ANALYSIS

After the factorial experiment was designed, the simulation model was used to run the treatment combinations. Table 13 shows the average results of the 1000 replications of each treatment combination.

Table 13. Experiment Factors and Average Responses

	Changing Factors				Responses		
TLC	CR	CV	ρ	SC	Average CO_2/Route (Kg)	Average Cost/Route ($)	Service Level (%)
1	0	0	0	0	128.00	125.43	100.00
2	1	0	0	0	128.01	125.43	100.00
3	2	0	0	0	146.08	139.03	86.08
4	0	1	0	0	127.02	124.98	99.74
5	1	1	0	0	138.11	132.58	93.39
6	2	1	0	0	176.20	160.41	66.12
7	0	2	0	0	133.48	129.27	95.33
8	1	2	0	0	158.47	146.57	80.08
9	2	2	0	0	188.26	168.00	61.81
10	0	0	1	0	128.00	125.43	100.00
11	1	0	1	0	128.01	125.43	100.00
12	2	0	1	0	146.08	139.03	86.08
13	0	1	1	0	127.06	125.00	99.40
14	1	1	1	0	138.15	132.60	93.08
15	2	1	1	0	176.27	160.44	65.88
16	0	2	1	0	133.55	129.31	94.50
17	1	2	1	0	158.53	146.61	79.41
18	2	2	1	0	188.39	168.07	61.27
19	0	0	2	0	128.00	125.43	100.00
20	1	0	2	0	128.01	125.43	100.00
21	2	0	2	0	146.08	139.03	86.08
22	0	1	2	0	127.08	125.00	99.14
23	1	1	2	0	138.18	132.61	92.84
24	2	1	2	0	176.34	160.48	65.69
25	0	2	2	0	133.57	129.33	93.92
26	1	2	2	0	158.61	146.66	78.91

27	2	2	2	0	188.42	168.10	60.92
28	0	0	0	1	122.59	122.64	100.00
29	1	0	0	1	122.59	122.64	100.00
30	2	0	0	1	138.90	135.10	86.73
31	0	1	0	1	123.61	123.09	99.94
32	1	1	0	1	131.78	128.51	94.97
33	2	1	0	1	169.07	155.93	66.79
34	0	2	0	1	129.60	126.79	96.33
35	1	2	0	1	152.34	142.32	82.31
36	2	2	0	1	184.34	165.36	61.83
37	0	0	1	1	122.59	122.64	100.00
38	1	0	1	1	122.59	122.64	100.00
39	2	0	1	1	138.90	135.10	86.73
40	0	1	1	1	123.63	123.10	99.80
41	1	1	1	1	131.81	128.53	94.84
42	2	1	1	1	169.11	155.95	66.69
43	0	2	1	1	129.64	126.81	95.78
44	1	2	1	1	152.40	142.35	81.83
45	2	2	1	1	184.43	165.40	61.46
46	0	0	2	1	122.59	122.64	100.00
47	1	0	2	1	122.59	122.64	100.00
48	2	0	2	1	138.90	135.10	86.73
49	0	1	2	1	123.64	123.11	99.68
50	1	1	2	1	131.84	128.54	94.71
51	2	1	2	1	169.17	155.98	66.58
52	0	2	2	1	129.66	126.82	95.40
53	1	2	2	1	152.43	142.36	81.48
54	2	2	2	1	184.46	165.42	61.22

5.1 Carbon Dioxide Emissions

The ANOVA table for carbon dioxide emissions can be observed in Table 14. The ANOVA table is used to determine the impact of the different factors in relation to the response being analyzed. To explain the information found in the ANOVA table the data for the factor “system configuration” is used as an example. The first column “DF” represents the degrees of freedom which is equal to the levels of the factor minus one. The next two columns are the residual sum of squares and the mean square error. The

adjusted mean square error is equal to the sum of squares divided by the degrees of freedom. The F statistic derives from the division of the mean square by the mean square error.

Table 14. ANOVA Table for Average CO_2 Emissions per Route.

Analysis of Variance for Average CO_2 Emissions / Route, using Adjusted Ss for Tests						
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
System Configuration	1	398961	398961	398961	77339.25	0.000
CR	**2**	**15156668**	**15156668**	**7578334**	**1469072.19**	**0.000**
CV	**2**	**6455111**	**6455111**	**3227556**	**625666.83**	**0.000**
SC	2	35	35	18	3.43	0.032
System Configuration*CR	2	9584	9584	4792	928.96	0.000
System Configuration*CV	2	4305	4305	2153	417.27	0.000
System Configuration*SC	2	1	1	1	0.11	0.896
CR*CV	**4**	**2600586**	**2600586**	**650146**	**126031.93**	**0.000**
CR*SC	4	3	3	1	0.16	0.960
CV*SC	4	20	20	5	0.97	0.422
System Configuration*CR*CV	4	10001	10001	2500	484.65	0.000
System Configuration*CR*SC	4	0	0	0	0.01	1.000
System Configuration*CV*SC	4	1	1	0	0.03	0.998
CR*CV*SC	8	2	2	0	0.06	1.000
System Configuration*CR*CV*SC	8	0	0	0	0.01	1.000
Error	53946	278285	278285	5		
Total	53999	24913564				
S = 2.27125 R-Sq = 98.88% R-Sq(adj) = 98.88%						

When analyzing the supply chain experiment design it can be determined by the ANOVA table that the main effects are the main contributors to the carbon dioxide emissions. Note that the value for the Adjusted Sum of Squares (Adj. SS) and Adjusted Mean Squares (Adj. MS) are rounded in the table, but the F statistics and P values are computed appropriately. From all the main effects, the factors that drive the carbon dioxide emissions are "capacity ratio" (CR) and "coefficient of variation" (CV). Even though the P values of the factors "system configuration" and "smoothing constant" (SC)

are statistically significant (smaller than 0.05), the adjusted mean square value for "system configuration" is one eighth the value of the coefficient of variation, furthermore the adjusted mean square value for "coefficient of variation" is five orders of magnitude bigger than the value for "smoothing constant." This difference in magnitude suggests that the factors are significant but perhaps not relevant. The system configuration factor seems significant most probably due to the great number of replications of the experiment, which results in a high value of degrees of freedom of the error term. Furthermore, the two way interaction of the factors "capacity ratio" and "coefficient of variation" appears to be significant and relevant. The two two-way interactions between the factors "system configuration" and "capacity ratio" and "system configuration" and "coefficient of variation" are also statistically significant but their low adjusted mean square suggests their effects are perhaps not relevant. This is the same case for the three-way interaction between "system configuration," "capacity ratio," and "coefficient of variation." The rest of the three and four way interactions are not statistically significant. The high value of R-Sq value (98.88%) shows that the statistical model has a high predicting power.

The impact of the significant factors can be observed by analyzing the main effect plot for carbon dioxide emissions (see Figure 21). When "capacity ratio" increases, the carbon dioxide emissions of the system also increase. The steepest part of the line can be observed as the "capacity ratio" moves from 70% to 90%, depicting that when the capacity ratio is closer to 1 (100%) the carbon dioxide emissions increment at a higher rate.

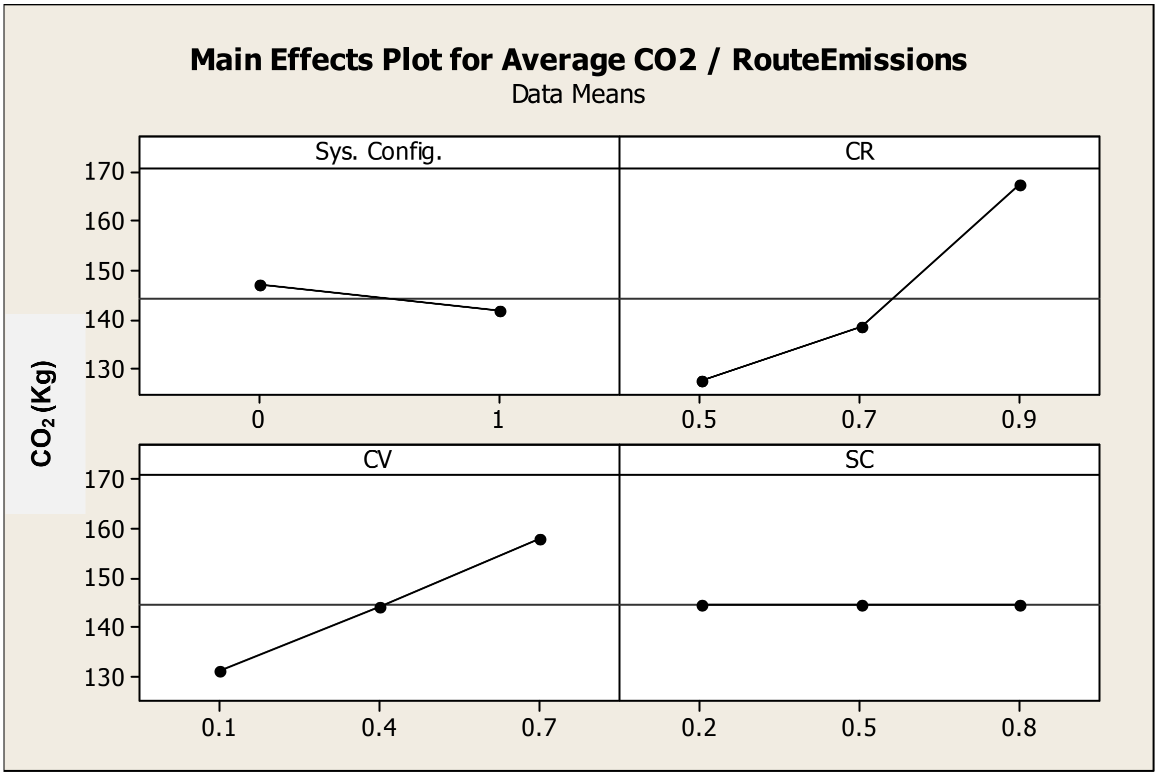

Figure 21. Main Effects Plot for Average CO_2 Emissions per Route (CO_2 Kg)

When the "capacity ratio" increases from 50% (127.41 Kg) to 70% (138.58 Kg) the increment is 11.18 Kg whereas when the increase is from 70% (138.58 Kg) to 90% (167.19 Kg) the increment is 28.61Kg. The ratio between the increments is 2.5; this suggests that the impact on the carbon dioxide emissions is 2.5 higher when the "capacity ratio" increases from 70% to 90%. This behavior can be explained by considering that when the system is at 50% "capacity ratio" there is extra loading capacity available in the trucks and it is not necessary to make more than one trip to fulfill the demand. On the other hand, when "capacity ratio" is 90%, the cases in which more than one trip is required to deliver the product increases because the space in the truck is very limited.

The main effect plot in Figure 21 shows that carbon dioxide emissions are positively correlated with the factor "coefficient of variation." The increments in carbon

dioxide emissions between the levels of the “coefficient of variation” were calculated to further analyze their impact. The increment between the level 10% (131.03 Kg) and 40% (144.34 Kg) was 13.31Kg and between the level 40% (144.34 Kg) and 70% (157.81 Kg) was 13.47Kg, the difference between the increments is 0.16 which represents an increment of 1%, this small difference may suggest that changes in the level of the factor will result in proportional increase in carbon dioxide emissions. This effect is logical because the demand always has the same average value and when the “capacity ratio” increases it also increases the standard deviation of the demand. A proportional increase in standard deviation means that the probability of the demand being greater than the loading capacity of the truck increases as well, therefore more trips are required to deliver the product.

The factor “system configuration” has statistical significance as shown in the ANOVA table (see Table 14). The slight differences between the low and high level can be explained considering that with a bigger system, there are more trucks that can be assigned to the routes, therefore the assignment of trucks may be more efficient. When comparing the two factors “capacity ratio” and “coefficient of variation” against “system configuration” the impact seems to be not relevant on the carbon dioxide emissions. The increase of carbon dioxide emissions under these assumptions is mostly driven by the variability of the demand affected by the factor “coefficient of variation” and the level of capacity of the system affected by the factor “capacity ratio.”

The interaction plot gives a better insight to the statistically relevant two-way interaction, “capacity ratio” with “coefficient of variation”, shown in the ANOVA table (see Figure 22). Analyzing the interaction plot of the factors “capacity ratio” and

“coefficient of variation” it can be observed that when the system is at 50 % capacity the impact of demand variance on the carbon dioxide emissions is lower because it can be better assimilated. When the capacity ratio is at its low level (50%) the trucks have significant extra capacity, under this scenario the variance in demand can be managed without having to incur extra trips for the distribution of product. It can be observed that as the “capacity ratio” increases, the slope of the lines also increases. This implies that when the system is closest to its full capacity (90%) the changes in demand variance have a higher impact in the production of carbon dioxide emissions. The impact increments because the trucks are very close to their full capacity and small increments in demand may require more than one trip. The other interaction plots have parallel lines that signify that the direction and impact of the factors does not change in relation with the other factors.

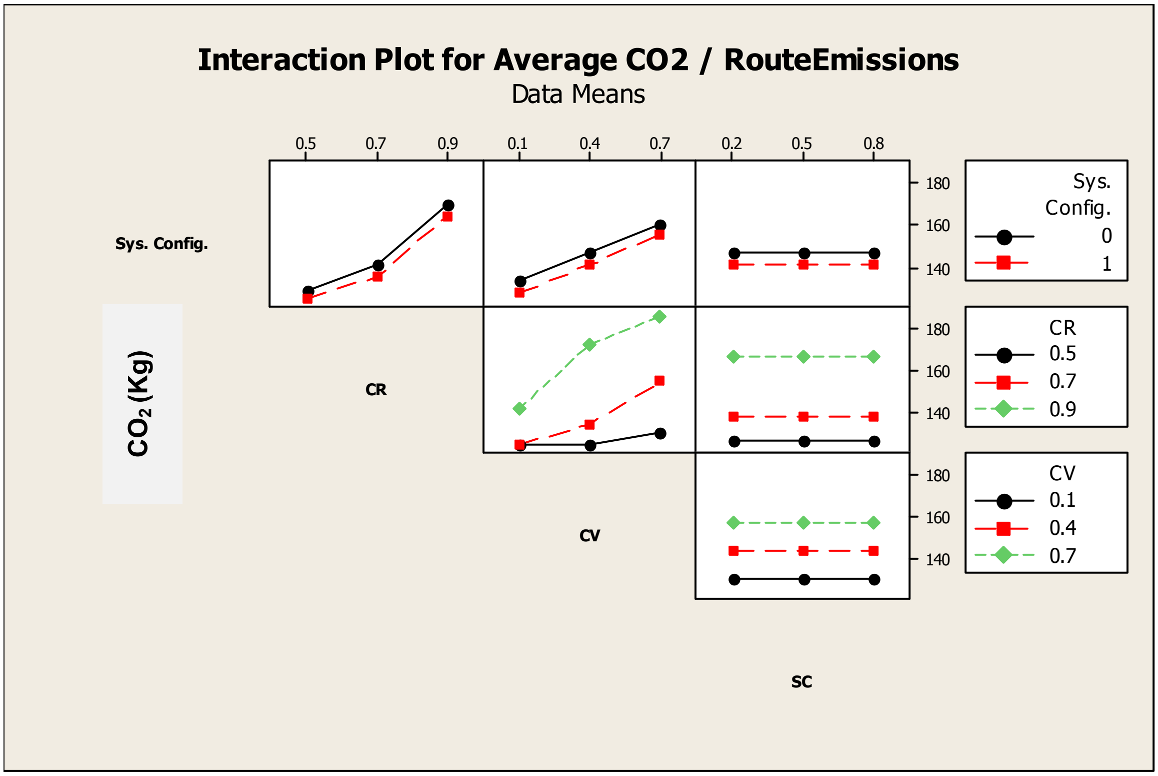

Figure 22. Two Factor Interaction Plot for Average CO_2 Emissions per Route (CO_2 Kg)

The residual plot for average carbon dioxide emissions was used to examine the validity of the underlying ANOVA assumptions (see Figure 23). The normality plot and the histogram suggest that the residuals are not normally distributed, suggesting that the normal distribution is not a good fit for the data set. Because the data is not normally distributed the F statistic will not be used to determine the relevance of the factors, the analysis will mostly rely on the value for the adjusted mean squares. It can be observed in the residual plot graph of "Residuals vs. Fitted Values" that the residual variance increases as the magnitude of the fitted values increase. The graph of "Residuals vs. Order" shows that the residuals are grouped together because the treatment combinations of the experiment were not randomized.

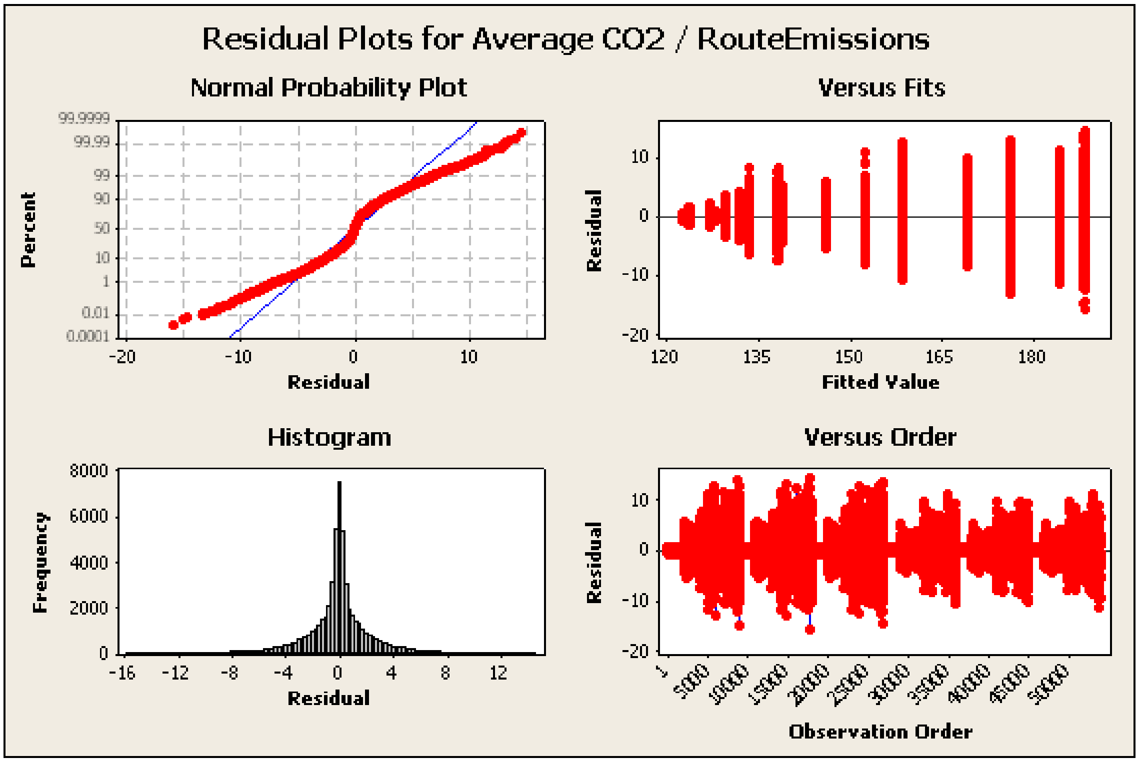

Figure 23. Main Effects Plot for Average CO_2 Emissions per Route

5.2 Cost

The ANOVA table for cost can be observed in Table 15. Based on the ANOVA table it can be determined that the cost is driven by the main effects. Besides the main effects, the two-way interactions of "system configuration" and "capacity ratio", "system configuration" and "coefficient of variation", and "capacity ratio" and "coefficient of variation" appear to be statistically significant based on their P value. When comparing the value of their adjusted mean square with the main effects, the only two-way interaction that appears to be relevant is between the factors "capacity ratio" and "coefficient of variation". The three-way interaction between "system configuration,""capacity ratio," and "coefficient of variation" has a significant impact

statistically but its low adjusted mean square value may suggest that its impact is not relevant.

From the main effects, the factor "capacity ratio" produces the biggest impact on cost. As with carbon dioxide emissions, when the system is closer to its total capacity (100%) the probability that small increases in demand result in more than one trip to deliver the product increases. When the number of trips increase, more labor and fuel is required, therefore the cost increases. The second factor that has a significant impact on the response cost is the "coefficient of variation". The factor "coefficient of variation" increases the variance of the demand perceived by the wholesaler. A high demand variance results in higher probabilities that the demand will exceed the loading capacity of the truck. When this happens, more trips are required to deliver product and an increase in the number of trips also increases the cost of the route.

Table 15. ANOVA Table for Average Cost per Route.

Analysis of Variance for Average Cost / Route, using Adjusted SS for Tests						
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
System Configuration	1	143967	143967	143967	56497.97	0.000
CR	**2**	**7903389**	**7903389**	**3951694**	**1550785.78**	**0.000**
CV	**2**	**2930607**	**2930607**	**1465303**	**575037.25**	**0.000**
SC	2	9	9	4	1.75	0.173
System Configuration*CR	2	5143	5143	2571	1009.13	0.000
System Configuration*CV	2	323	323	161	63.31	0.000
System Configuration*SC	2	1	1	0	0.12	0.886
CR*CV	**4**	**1241331**	**1241331**	**310333**	**121785.60**	**0.000**
CR*SC	4	1	1	0	0.12	0.976
CV*SC	4	6	6	1	0.56	0.690
System Configuration*CR*CV	4	4860	4860	1215	476.83	0.000
System Configuration*CR*SC	4	0	0	0	0.01	1.000
System Configuration*CV*SC	4	1	1	0	0.06	0.993
CR*CV*SC	8	1	1	0	0.04	1.000
System Configuration*CR*CV*SC	8	0	0	0	0.01	1.000
Error	53946	137465	137465	3		
Total	53999	12367102				
S = 1.59630 R-Sq = 98.89% R-Sq(adj) = 98.89%						

When considering the main effect plot for average cost per route the impact of the factors is similar to the ones observed for the average carbon dioxide emissions (see Figure 24). The main effect plot shown in Figure 24 was analyzed to better understand the relation between the relevant factors and average cost per route. The factor “capacity ratio” shows the same behavior with the response cost as it does with the response carbon dioxide emissions. When calculating the differences between the points of the different levels of the factor it can be observed that the difference between the level 50% ($ 125.38) and the level 70% ($ 133.02) is 7.65 and between the level 70% ($ 133.02) and 90% ($ 154.00) is 20.97. With a ratio of 2.74 between the differences, it can be determined that cost not only increments when the capacity ratio of the system increments, but also that the size of the impact increases as “capacity ratio” increases. The main effect plot of the factor “coefficient of variation” was also analyzed. The difference between the level 10% ($ 128.38) to 40% ($ 137.60) is 9.23 and between the level 40% ($ 137.60) and 70% ($ 146.42) is 8.82. The similarities between the increments (difference of 0.41) may suggest that the impact of the factor “coefficient of variation” is proportional to the increment of the factor itself.

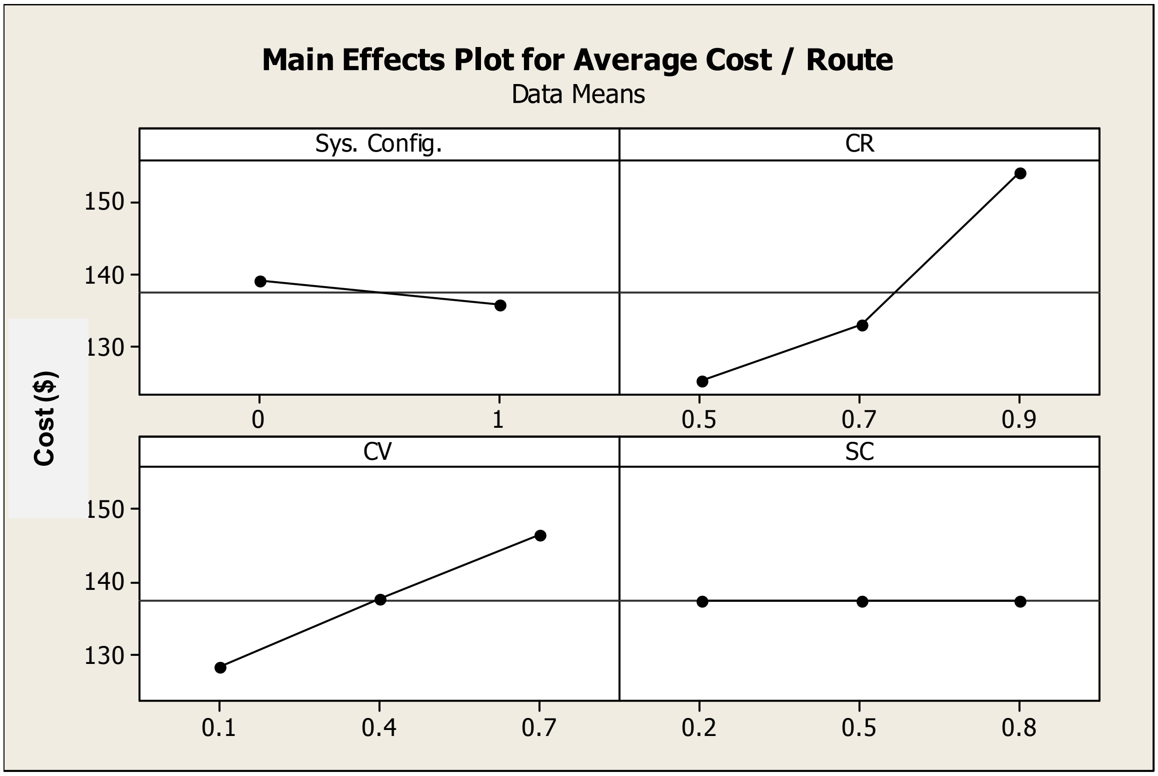

Figure 24. Main Effects Plot for Average CO_2 Emissions per Route ($)

The interaction plot for average cost per route in Figure 25 shows the interaction between the factors “coefficient of variance” and “capacity ratio”. To better analyze the two way interaction, the data was organized in the nine possible treatment combinations (3^2) of the factors “capacity ratio” and “coefficient of variation”, calculating the average value for each response (see Table 16).

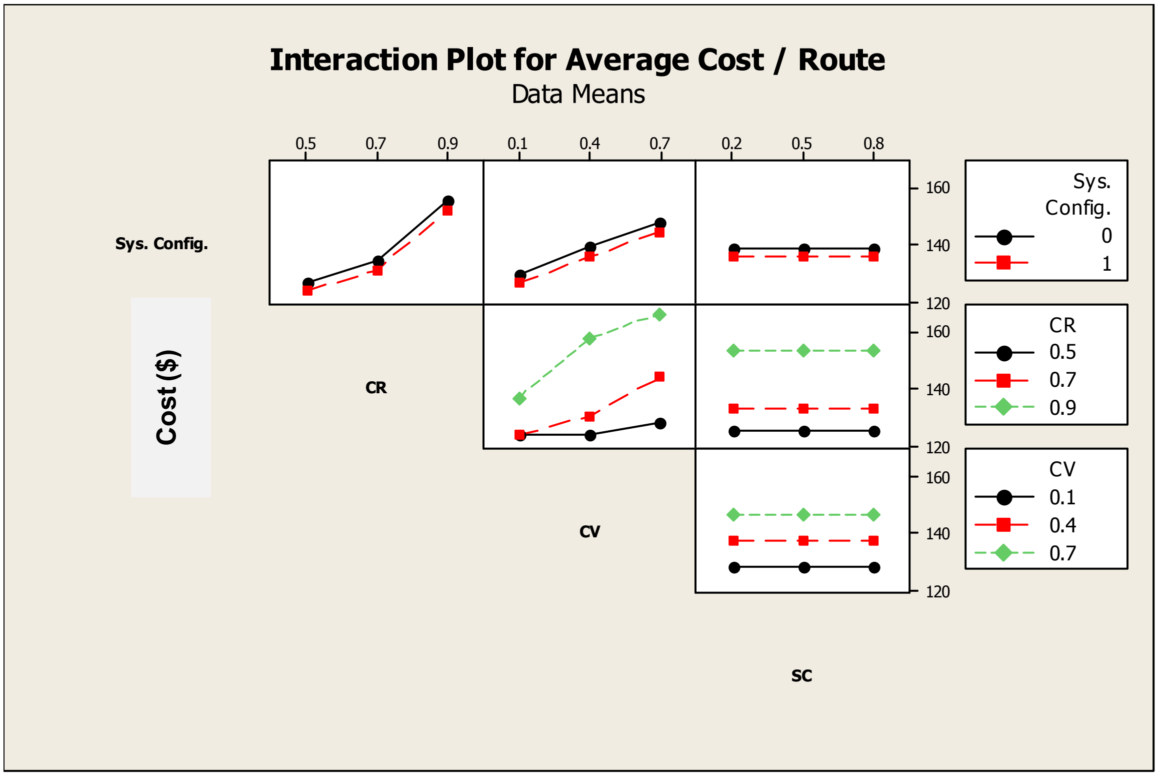

Figure 25. Interaction Plot for Average Cost per Route ($)

Table 16. Interaction Between CR and CV in Relation to Average CO_2, Cost and Average Trips per Route.

CR	CV	Average CO_2/Route (Kg)	Average Cost/Route ($)	Average Trips per Route
0.5	0.4	127.08	125.00	1.00
0.5	0.1	128.00	125.43	1.00
0.7	0.1	128.01	125.43	1.00
0.5	0.7	133.57	129.33	1.03
0.7	0.4	138.18	132.61	1.06
0.9	0.1	146.08	139.03	1.14
0.7	0.9	158.61	146.66	1.19
0.9	0.4	176.34	160.48	1.34
0.9	0.9	188.42	168.10	1.39

The data of the two-way interaction in relation to carbon dioxide emissions and cost is graphed in two 3-D surface plots shown in Figure 26 and Figure 27. The average

number of trips was also calculated and is used later in this section for further analysis. The 2-D interaction graph between “capacity ratio” and “coefficient of variation” can be seen for the interaction plot of carbon dioxide emissions in Figure 22. In the 3-D graphs the lighter the tone of the graph the highest the emissions of carbon dioxide and cost. On the other hand the darker color represents low and medium carbon dioxide emissions and cost. It can be observed that for the treatment combinations in which the factor “capacity ratio” is at its lowest level (50%) the factor “coefficient of variation” has a very low impact on the responses cost and carbon dioxide emissions. The 3-D graph shows that at 50% capacity ratio the lowest level of carbon dioxide emissions and cost can be observed. On the other hand, when the “capacity ratio” increases to 70% the system is more sensitive to the variance of the demand. It can be observed that the area of the graph representing 70 % changes to a darker tone which means that there is an increment in the values for carbon dioxide emissions and cost. Finally, when the capacity ratio is at its highest level (90%) the ratio in which the responses increase is higher. This can be verified by the 3-D graph in which the lines that represent 90 % capacity ratio move from the lower area of the graph (lower carbon dioxide emissions and cost) at 10% coefficient of variation to the highest point (higher carbon dioxide emissions and cost) when the coefficient of variation increases to 70%. This happens because when the demand variability increases from the low to the medium level, the swings in demand increases the demand enough so that more than one trip is required to deliver the product. The increment of the responses between the low and medium level is higher than the increment between the medium and high level of the “coefficient of variation.” This can be observed because at the medium level of variance the truck is already required to

make two trips to deliver product and at the high level the swings in demand increase the probability of two trips except for when the swings in demand require three trips, but the instances in which this happens is low. Observing Figure 26 and Figure 27 it can be concluded that when the factors "coefficient of variation" and "capacity ratio" are at their highest levels the carbon dioxide emissions and cost are also at their highest level.

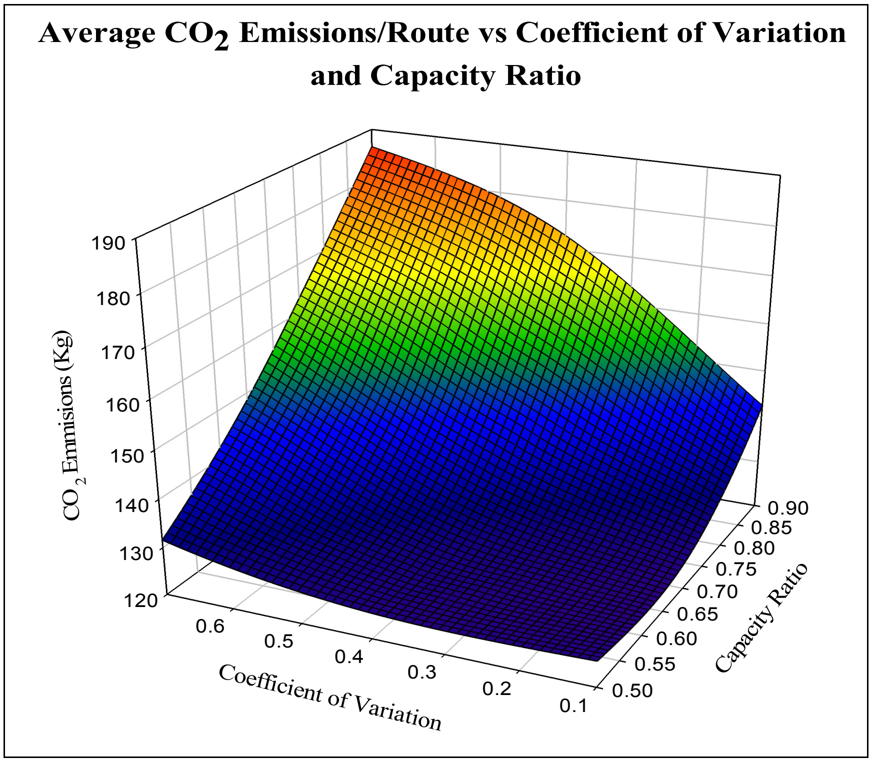

Figure 26. Average CO_2 per Route vs. CV and CR

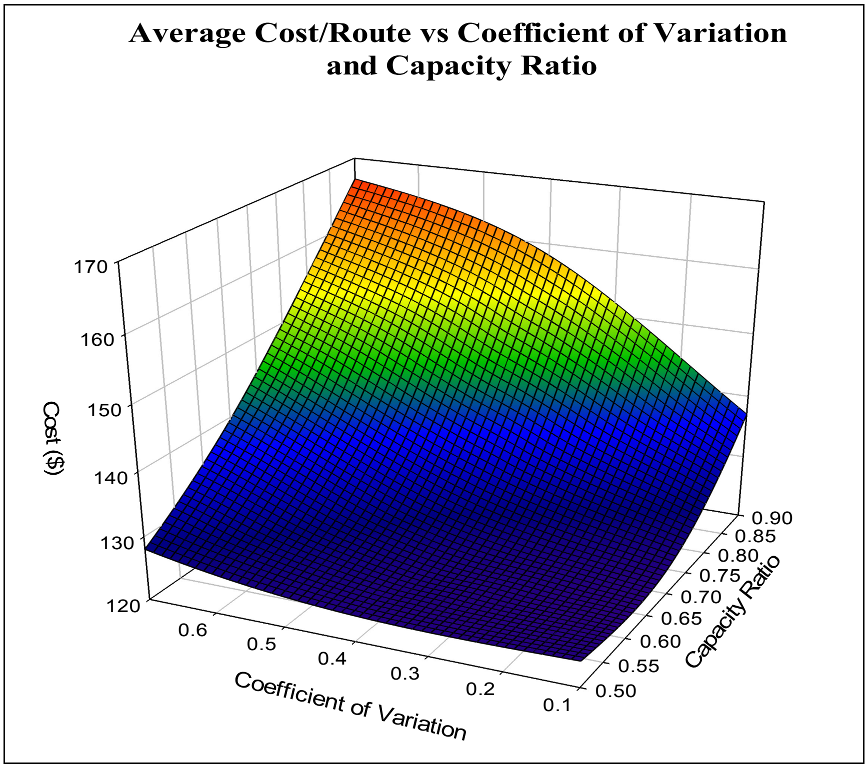

Figure 27. Average Cost per Route vs. CV and CR

The impact of the factors "capacity ratio" and "coefficient of variation" affect the responses carbon dioxide emissions and cost in a similar way (see Figure 21 and Figure 24). Under this supply chain design and assumptions, variables that relate to the calculation of cost and carbon dioxide emissions are labor and gallons of fuel consumed, both are calculated based on the number of trips required to deliver product. The logic used to explain their effect suggests that when the number of trips required for the delivery of product increases, the carbon dioxide emissions and the cost of the route also increase. To demonstrate this, the data from the two-way interaction between capacity ratio and coefficient of variation for carbon dioxide emissions and cost was graphed against the average number of trips (see Table 16). The graphs in Figure 28 and Figure 29 show that cost and carbon dioxide emissions are strongly correlated with the increment in

trips required to deliver product. The correlation was not surprising, but it helped support the explanations made in this study. The correlation factor R, for the correlation between carbon dioxide emissions and average number of trips and for the correlation between cost and average number of trips, are 0.99 and 0.99 respectively. The slope of the trend line corresponding to average carbon dioxide emissions is 107.86 and the slope for average cost is 151.62. Under the assumptions of this research, the slopes suggest that for every extra trip, approximately 107.86 kg of carbon dioxide are emitted and $ 151.26 are spent by the wholesaler.

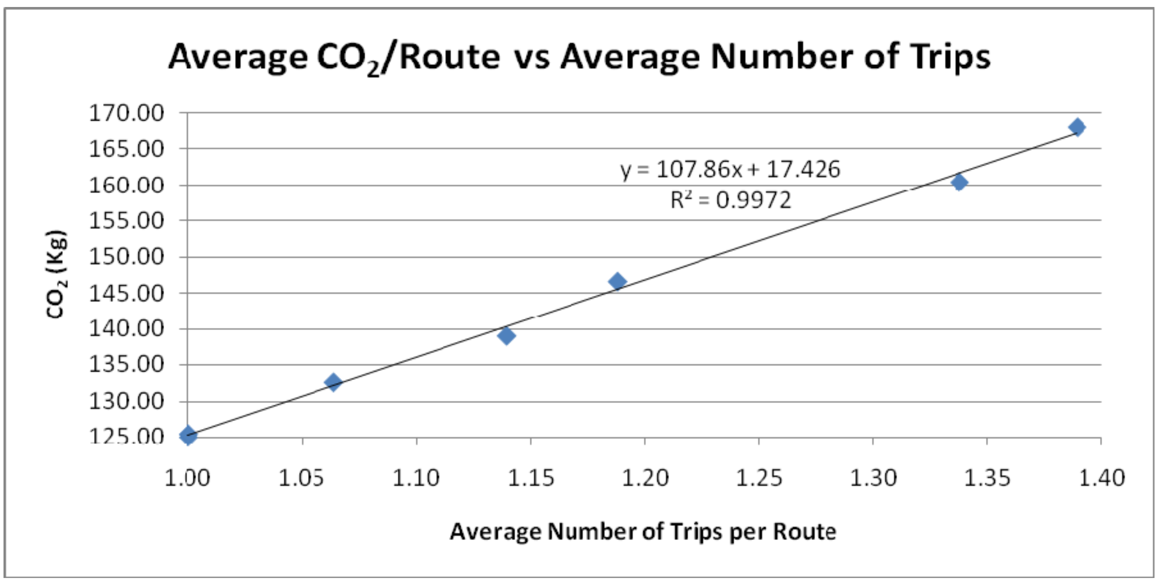

Figure 28. Average CO_2 Emissions per Route vs. Average Number of Trips per Route

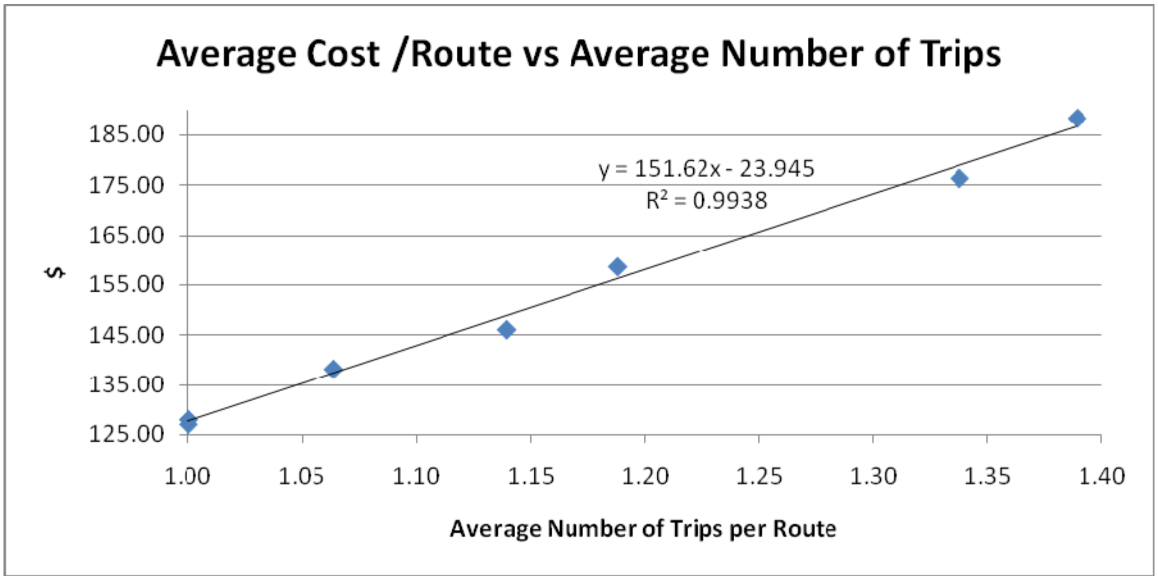

Figure 29. Average Cost per Route vs. Average Number of Trips per Route

Total cost can be divided into labor cost and diesel cost; under the assumptions made in this model the data shows that the major contributor to the total cost is labor cost. Table 17 shows the treatment combinations of the two main factors, "capacity ratio," and "coefficient of variation," with their total average cost as well as the division of diesel cost and labor cost. Although labor cost is the major contributor to total cost, the cost that increases the most in relation to the increase of average trips per route is diesel cost. The average number of trips per route is calculated dividing the sum of all the trips made divided by the total number of routes serviced. When the average number of trips increase from 1.00 ($ 36,899) to 1.39 ($ 53,289) there is a difference in diesel cost of $ 16,390. For labor cost, when the average number of trips increase from 1.00 ($ 44,326.) to 1.39 ($ 53,426) the difference is $ 9,100. Under the assumptions of this model, the increase in average trips per route has a greater impact on diesel cost than on labor cost, this impact can be easily observed in Figure 30.

Table 17. Total Cost

CR	CV	Total Cost ($)	Diesel Cost ($)	Labor Cost ($)	Average # of Trips
0.5	0.4	80720.59	36556.89	44163.70	1.00
0.5	0.1	81527.89	37070.32	44457.57	1.00
0.7	0.1	81430.99	37071.38	44359.61	1.00
0.5	0.7	82069.62	37760.56	44309.06	1.03
0.7	0.4	85626.91	39747.30	45879.61	1.06
0.9	0.1	90367.41	42305.92	48061.49	1.14
0.7	0.9	93079.03	44843.03	48236.00	1.19
0.9	0.4	103615.95	50719.25	52896.70	1.34
0.9	0.9	106716.94	53289.98	53426.97	1.39

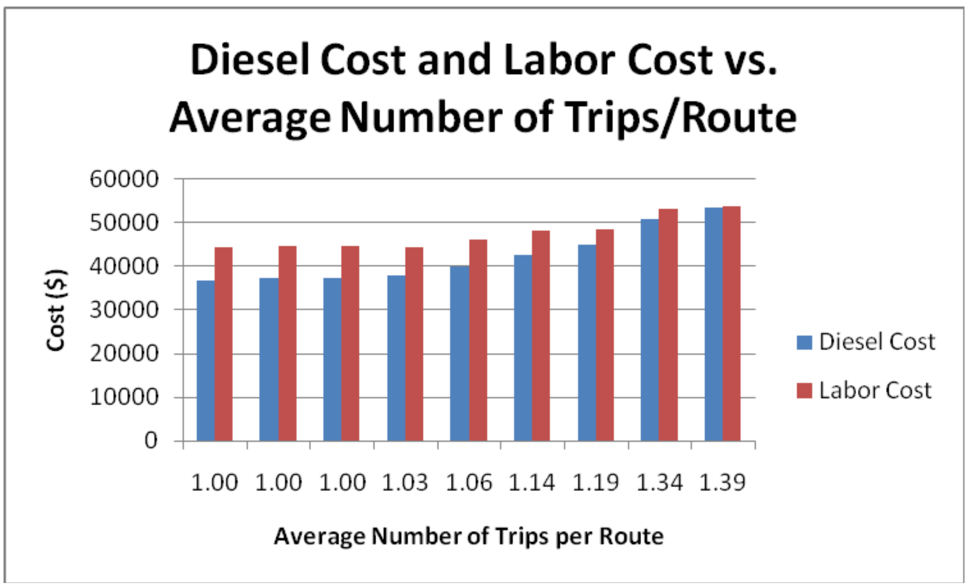

Figure 30. Diesel Cost and Labor Cost vs. Average Number of Trips

5.3 Service Level

The resulting ANOVA table for service level is shown in Table 18. It is important to mention that the service level decreases when two events happen, lack of inventory to fulfill orders and more than one trip required to deliver product. Analyzing the ANOVA

table it can be determined that the factor “capacity ratio” and the factor “coefficient of variation” drive service level, based on the adjusted mean square value.

Table 18. ANOVA Table for Service Level.

Analysis of Variance for Service Level, using Adjusted SS for Tests						
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
System Configuration	1	0.909	0.909	0.909	3411.04	0.000
CR	**2**	**705.795**	**705.795**	**352.898**	**1323838.05**	**0.000**
CV	**2**	**241.61**	**241.61**	**120.805**	**453179.79**	**0.000**
SC	2	0.186	0.186	0.093	349.70	0.000
System Configuration*CR	2	0.211	0.211	0.105	395.08	0.000
System Configuration*CV	2	0.267	0.267	0.133	500.07	0.000
System Configuration*SC	2	0.011	0.011	0.005	20.08	0.000
CR*CV	**4**	**94.744**	**94.744**	**23.686**	**88853.89**	**0.000**
CR*SC	4	0.005	0.005	0.001	4.49	0.001
CV*SC	4	0.146	0.146	0.037	137.04	0.000
System Configuration*CR*CV	4	0.352	0.352	0.088	330.15	0.000
System Configuration*CR*SC	4	0	0	0	0.46	0.764
System Configuration*CV*SC	4	0.006	0.006	0.001	5.29	0.000
CR*CV*SC	8	0.005	0.005	0.001	2.21	0.024
System Configuration*CR*CV*SC	8	0	0	0	0.15	0.997
Error	53946	14.38	14.38	0		
Total	53999	1058.627				
S = 0.0163270 R-Sq = 98.64% R-Sq(adj) = 98.64%						

The main effects plot confirms that the factors that have the bigger impact on the service level are the “capacity ratio” and “coefficient of variation” (see Figure 31). Additionally, it can be observed that when these factors increase, service level decreases. The effect of the factors “capacity ratio” and “coefficient of variation” on service level make sense because a system that is closer to 100% percent capacity is more likely to encounter difficulties when meeting demand and delivering product to the retailers than a system at lower capacity. It was shown in the previous section that the factors “capacity

ratio” and “coefficient of variation” increase the number of trips required to deliver product, which under the assumptions of this model reduce the service level.

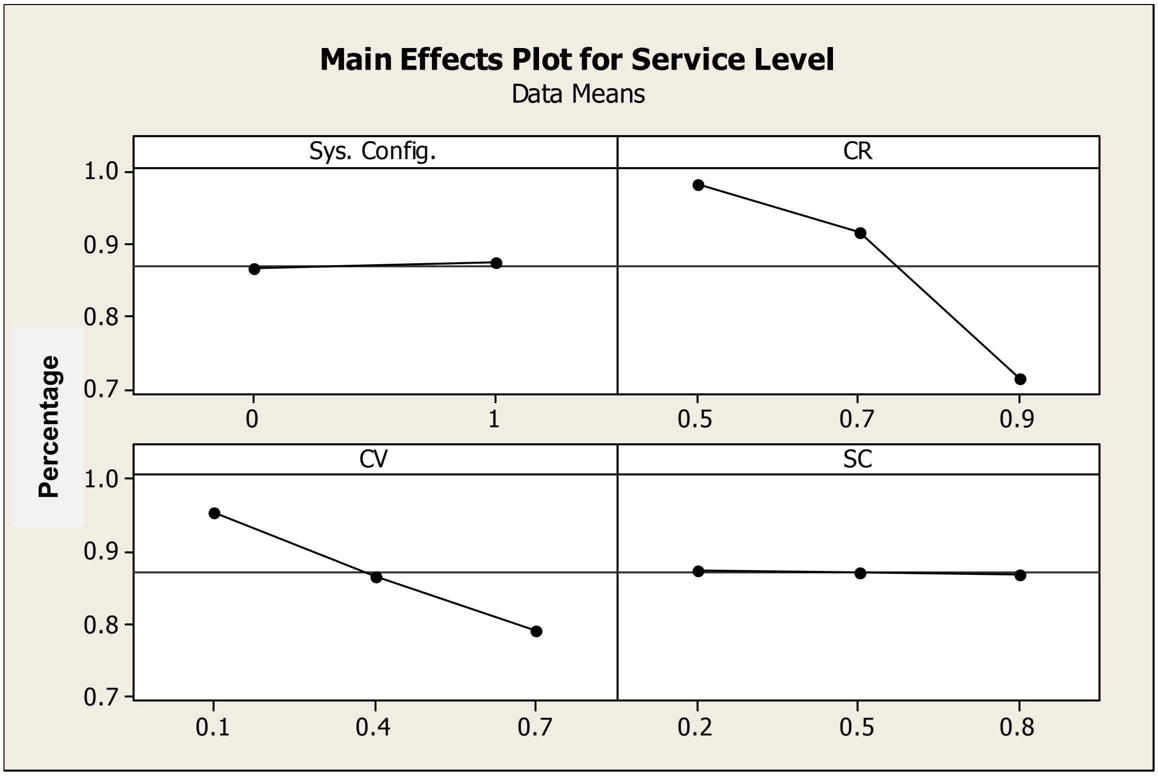

Figure 31. Main Effects Plot for Service Level

The main effect plot of the “capacity ratio” shows that the impacts of the medium and low level are not proportional. It can be calculated that the decrease of service level for the lines between the points of 50% (98%) to 70% (92%) and the points of 70% (92%) to 90% (71%) capacity is 6% and 21% respectively. The factor coefficient of variation also affects the service level because it is directly related to the swings in demand. When the variance level is low the increase in demand has a bigger probability of being within the capacity range of the truck. On the other hand, when demand variance increases, the probability of the demand being bigger than the capacity of the truck

increases, and therefore the service level decreases. The negative slope of the main plot shows that when the coefficient of variance increases the service level decreases.

It was originally assumed that the smoothing constant of the forecast would be significant because an inaccurate forecast should result in lack of inventory to fulfill the orders, which would lead to a lower service level based on the definition used in this research. The reason why the lack of inventory was not significant in the experiment was because the instances in which more than one trip was required to deliver the product was much higher in proportion to the lack of inventory. The data shows that when the service level reaches its lowest value in the experiment, 60.92%, only 2.98 % was due to lack of inventory on hand to fulfill the order, suggesting that forecast is not as relevant as the other factors.

All two-way and three way interactions, except the interaction between “”system configuration,”“capacity ratio,” and “smoothing constant,” are significant in the ANOVA table, but comparing their adjusted mean square values suggests that the only interaction that might be relevant is between “capacity ratio” and “coefficient of variation”. The relation of the factors can be observed in the interaction plot in Figure 32. The two-way interaction of the factors with respect to service level is the inverse of the same two-way interaction in relation to carbon dioxide emissions and cost. This can be explained considering that the factors contribute to the increase in average trips required to deliver product. The graph has the inverse form because an increase in the average number of trips increases carbon dioxide emissions and decreases service level.

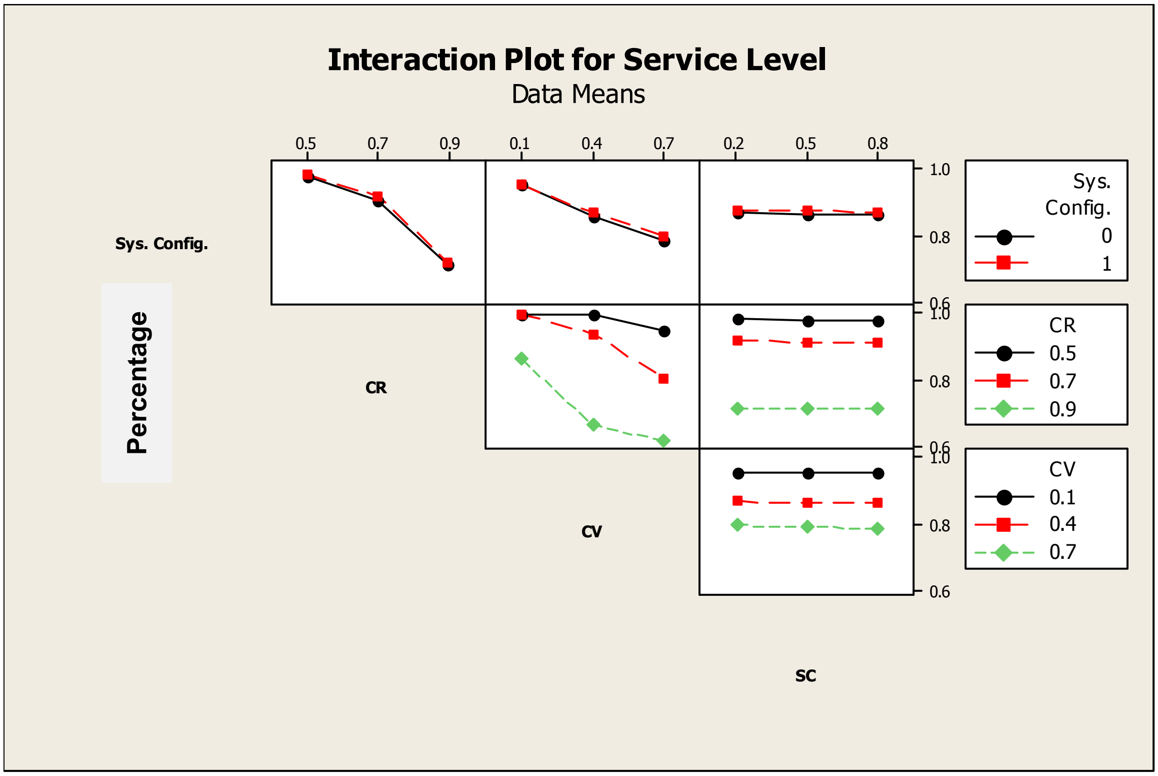

Figure 32. Two-way Interaction Plot for Service Level

The results of this analysis in relation to the factor "system configuration" may suggest that it may not have a relevant effect on average carbon dioxide emissions per route, average cost per route and service level. Based on this information it may be concluded that this research can be used as a tool to analyze systems of different sizes. The responses for cost, carbon dioxide emissions, and service level are strongly correlated to the number of trips required to deliver product. The number of trips made by the trucks depends on the loading capacity of the trucks and the amount of truck of each type in the fleet. Smaller trucks have less loading capacity and may result in making more trips but on the other hand smaller trucks have better efficiency and consume less fuel. This may suggest that the fleet configuration used by the wholesaler may have a great impact on the results. Further analysis was done to determine the importance and effect

of different fleet configurations under different scenarios. Under this logic and to better understand the impact of using different fleet configurations and possible tradeoffs between responses, another experiment was conducted.

5.4 Analysis and Results of Fleet Configuration

A second experiment was run with a fixed level for the factors "smoothing constant" and "system configuration" because they were found not to have a relevant effect (see Appendix B). Both factors are at their low level, the "smoothing constant" with a value of 0.2 and "system configuration" at the low level (10 trucks, 50 routes). In addition to the factor "capacity ratio" and "smoothing constant", the factor "fleet configuration" was added to represent the different fleet configurations. The three factors were used to create a $3^2 * 5^1$ full factorial design to analyze the responses. The experiment has 45 treatment level combinations; each of them was run for 1,000 replications. All the previous responses were recorded and analyzed. The factor "fleet configuration" has different levels that represent different possible combinations of truck types, but the total number of trucks used for distribution is always the constant so that comparisons can be made between fleet configurations (see Table 19).

Table 19. Levels of Factor Fleet Configuration

	Fleet Configuration (Total Trucks = 10)			
Level	Truck Type 1 (1000 cubes)	Truck Type 2 (1350 cubes)	Truck Type 3 (1650 cubes)	Total Loading Capacity (cubes)
A	5	5	0	11750
B	4	3	3	13000
C	3	4	3	13350
D	3	3	4	13650
E	0	5	5	15000

To better understand the different levels of the factor "fleet configuration" the total loading capacity of the fleet is also shown in Table 19. As it can be observed the difference in total loading capacity between the levels A and B is 1250 cubes, whereas between the levels B and C is 350 cubes. The main average responses in relation to the levels of the factor "fleet configuration" are shown in Table 20.

Table 20. Average Responses for Factor Fleet Configuration

Fleet Configuration	Average CO_2/Route (Kg)	Average Cost/Route ($)	Service Level	Average # of Trips
A	137.28	135.99	85%	1.15
B	155.81	141.23	91%	1.08
C	158.68	142.29	92%	1.08
D	164.45	144.59	93%	1.07
E	180.33	151.50	93%	1.07

5.4.1 Carbon Dioxide Emissions and Cost (Fleet Configuration)

With the ANOVA table for carbon dioxide emissions and cost it can be determined that the main effects have the higher statistical significance and drive the response (see Table 21 and Table 22). The three main effects, "capacity ratio," "coefficient of variation," and "fleet configuration," are statistically significant to the response carbon dioxide emissions. The ANOVA table and the main effect plot show that the impact of the main effects, "capacity ratio" and "coefficient of variation," have the same behavior of the original experiment, this demonstrates that their impact is independent from the truck fleet configuration (see Table 21, Table 22, Figure 33 and Figure 34). The relevance of the factor "fleet configuration" suggests that there is a difference in carbon dioxide emissions and cost based on the combination of trucks used

by the wholesaler to distribute product. All the main effects and interactions are statically significant when analyzed in the ANOVA table. As in the previous analysis, only the two-way interaction between the factors "capacity ratio" and "coefficient of variation" appears to be relevant to carbon dioxide emissions and cost, based on the comparison of the adjusted mean square values. This interaction was already explained in the previous sections.

Table 21. ANOVA Table for Average CO_2 Emissions per Route.

Analysis of Variance for Average CO_2 Emissions / Route, using Adjusted SS for Tests

Source	DF	Seq SS	Adj SS	Adj MS	F	P
CR	**2**	**7276180**	**7270821**	**3635410**	**682474.33**	**0.000**
CV	**2**	**4472069**	**4485211**	**2242605**	**421003.53**	**0.000**
Fleet Configuration	4	8718356	8721802	2180451	409335.22	0.000
CR*CV	**4**	**1556974**	**1557239**	**389310**	**73084.98**	**0.000**
CR*Fleet Configuration	8	162724	162844	20355	3821.33	0.000
CV*Fleet Configuration	8	36842	37641	4705	883.3	0.000
CR*CV*Fleet Configuration	16	198937	198937	12434	2334.15	0.000
Error	44955	239467	239467	5		
Total	44999	22661550				

S = 2.30799   R-Sq = 98.94%   R-Sq(adj) = 98.94%

Table 22. ANOVA Table for Average Cost per Route.

Analysis of Variance for Average Cost/Route, using Adjusted SS for Tests						
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
CR	**2**	**3421447**	**3420981**	**1710491**	**717474.32**	**0.000**
CV	**2**	**2060099**	**2057595**	**1028797**	**431534.53**	**0.000**
Fleet Config.	4	1150468	1152609	288152	120867.00	0.000
CR*CV	**4**	**705181**	**705134**	**176283**	**73943.02**	**0.000**
CR*Fleet Config.	8	163120	163377	20422	8566.17	0.000
CV*Fleet Config.	8	6584	6773	847	355.14	0.000
CR*CV*Fleet Config.	16	83544	83544	5222	2190.20	0.000
Error	44955	107175	107175	2		
Total	44999	7697619				
S = 1.54404 R-Sq = 98.61% R-Sq(adj) = 98.61%						

The main effect plot for the factor "fleet configuration" shows that the level of the factor that has the highest loading capacity has the highest carbon dioxide emissions and cost. This behavior can be explained based on the reduction of fuel efficiency of the trucks with higher loading capacity. Trucks with higher loading capacity result in fewer trips but the differences between fuel efficiency among trucks have a bigger impact than the number of trips made. The amount of fuel consumed by a truck type 1 with fuel efficiency of 8 mpg for a route 80 miles long is 10 gallons, in the same way the amount of fuel consumed by a truck type 3 with fuel efficiency of 4 mpg is 20 gallons. On the other hand, a truck type 1 has less loading capacity than a truck type 3, therefore the probabilities of having to make two trips to deliver product is higher. It can be observed in Table 23 that when the "fleet configuration" level is equal to E, the amount of gallons consumed is higher even though the average number of trips is lower than the rest levels.

Table 23. Fleet Configuration, Diesel Gallons Consumed, and Average Number of Trips

Fleet Configuration	Diesel Gallons Consumed	Average # of Trips
A	8778.72	1.15
B	9962.66	1.08
C	10145.87	1.08
D	10515.22	1.07
E	11530.99	1.07

In order to explain the impact of the factor "fleet configuration" shown in Figure 33 and Figure 34 it is important to consider that the levels are not equally spaced in relation to the total loading capacity of the trucks and the amount of each truck type. When looking at the levels B, C, and D it can be observed that the increment is constant, it is also observed that the difference between the levels is similar (between levels B and C is 300 cubes and between C and D is 350 cubes). On the other hand, the steep lines on both ends represent levels that have a much bigger difference in the loading capacity of the fleet than the middle three levels. The difference between level A and B is 1250 cubes and the difference between level D and E is 1350 cubes.

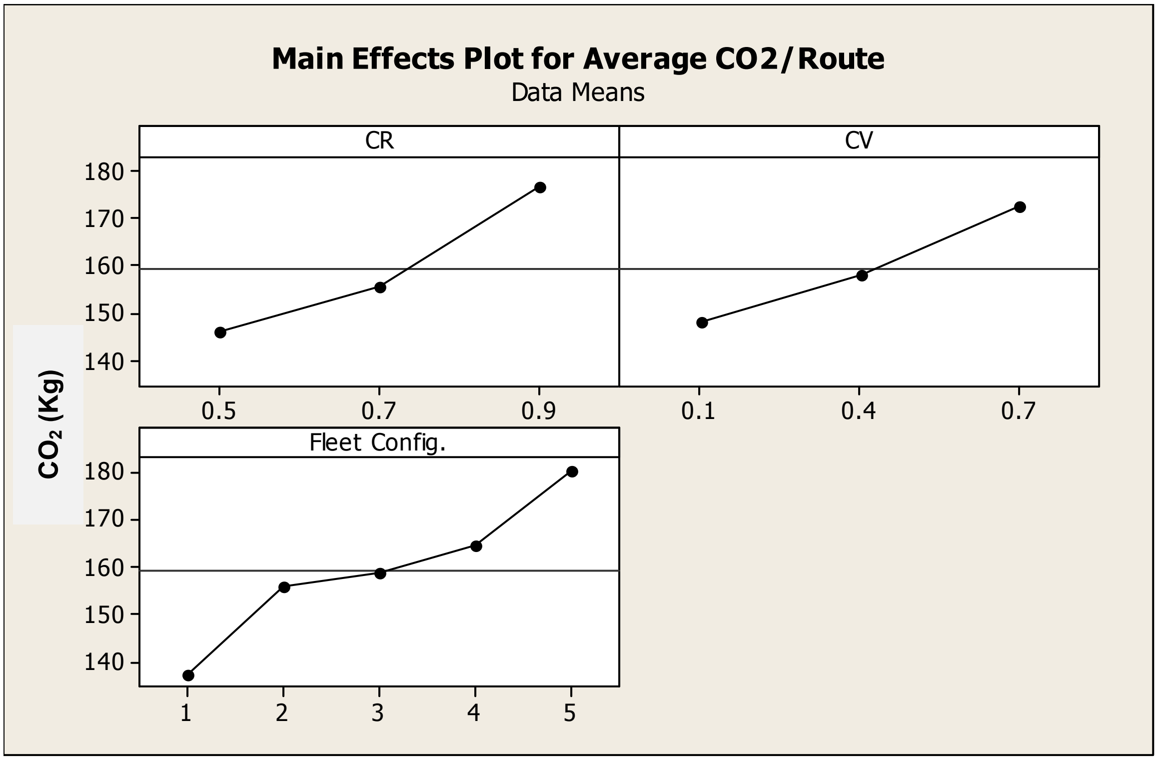

Figure 33. Main Effects Plot for Average CO_2 Emissions per Route

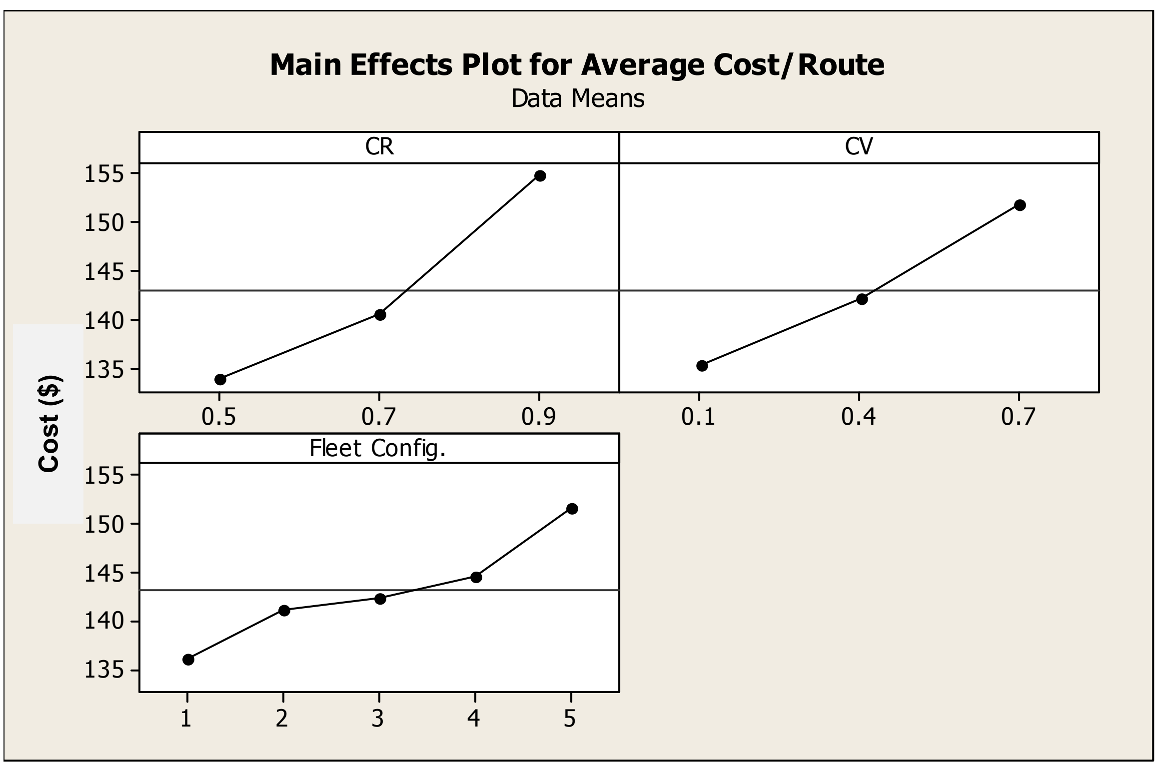

Figure 34. Main Effects Plot for Average Cost per Route

The analysis led to the conclusion that the average number of trips per route is positively correlated with the carbon dioxide emissions and cost. This conclusion still holds in this experiment, but only happens when the scenarios are compared using the same “fleet configuration”. When the comparison was done between the different “fleet configurations” the levels that resulted in lower average number of trips did not result in higher carbon dioxide emissions or cost (see Figure 35 and Figure 36). As a matter of fact it can be observed that the higher level of the factor “fleet configuration” results in fewer trips made. The reasoning for having an increase in cost and carbon dioxide emissions, even though less trips are being made, is that the trucks that are doing the trips have a much lower fuel efficiency therefore producing more carbon dioxide emissions than if more trips were made by the smaller trucks with higher fuel efficiency. Figure 35 and Figure 36 are not identical but the behavior of the responses carbon dioxide emissions and cost is very similar in this experiment also.

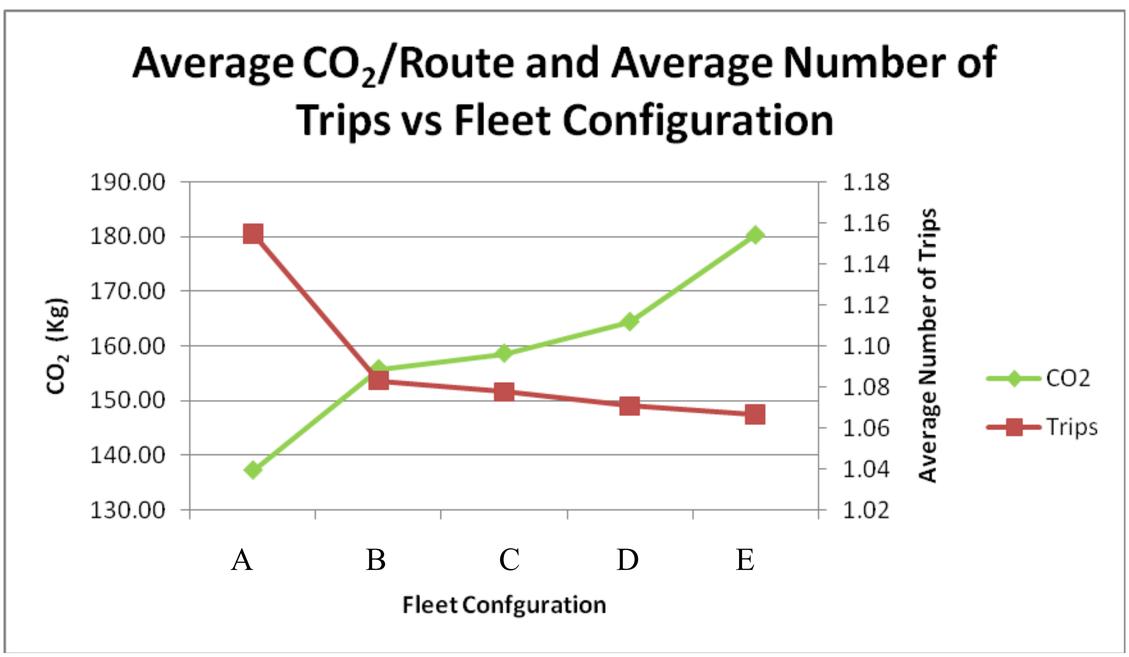

Figure 35. Average CO_2 Emissions per Route and Average Number of Trips vs. Fleet Configuration

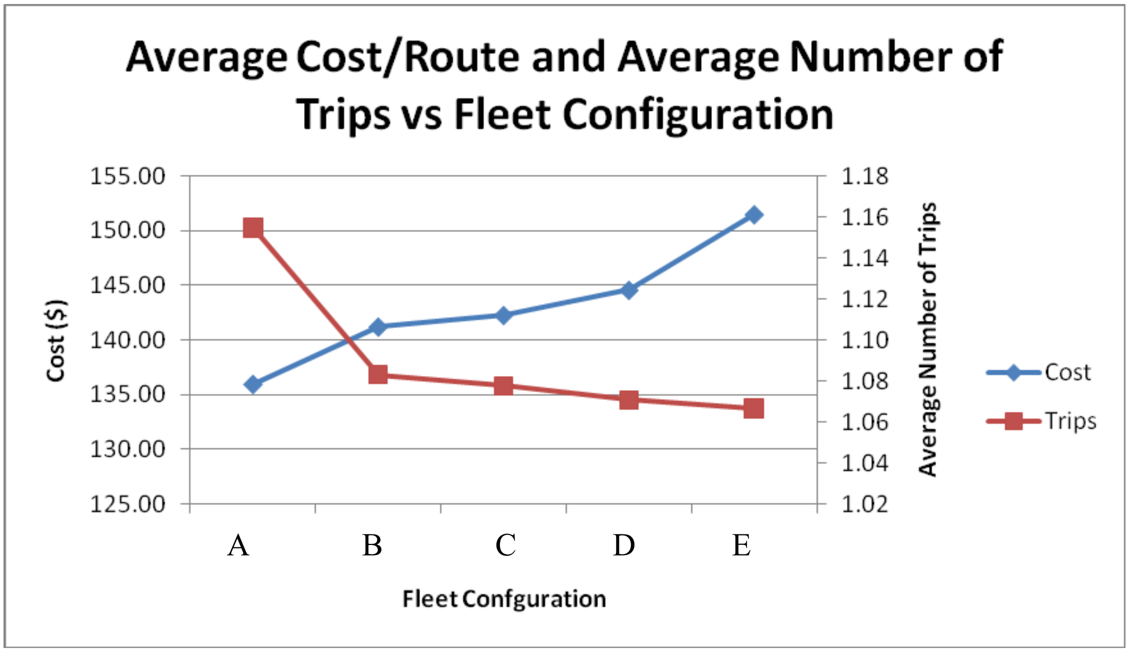

Figure 36. Average Cost per Route and Average Number of Trips vs. Fleet Configuration

5.4.2 Service Level (Fleet Configuration)

Besides the effects and interactions that have been analyzed previously, the ANOVA table shows that factor "fleet configuration" also appears to be relevant in relation to the response service level (see Table 24). All the rest of the interactions are statically significant, but the two-way interaction between the factors "capacity ratio" and "fleet configuration" appears to be more relevant than the rest, this behavior was previously explained in section 5.3.

Table 24. ANOVA Table for Service Level per Route.

Analysis of Variance for Service Level, using Adjusted SS for Tests						
Source	**DF**	**Seq SS**	**Adj SS**	**Adj MS**	**F**	**P**
CR	**2**	**223.298**	**223.461**	**111.731**	**578692.99**	**0.000**
CV	**2**	**155.956**	**154.683**	**77.342**	**400579.57**	**0.000**
Fleet Config.	4	42.963	42.835	10.709	55464.09	0.000
CR*CV	**4**	**41.263**	**41.244**	**10.311**	**53404.92**	**0.000**
CR*Fleet Config.	8	25.139	25.187	3.148	16306.65	0.000
CV*Fleet Config.	8	1.071	1.069	0.134	692.39	0.000
CR*CV*Fleet Config.	16	7.472	7.472	0.467	2418.68	0.000
Error	44955	8.68	8.68	0		
Total	44999	505.84				
S = 0.0138951 R-Sq = 98.28% R-Sq(adj) = 98.28%						

The main effect plot for service level shows that when the factor "fleet configuration" is at the highest level the service level also increases. When looking at the data, it can be explained that at the highest level (E) of the factor "fleet configuration" the average number of trips is 1.07, whereas at the lowest level (A) the average number of trips is 1.15. The difference in service level between fleet configuration two and four is 2% (91% to 93%) (see Figure 37). Additionally, the two-way interaction plot depicts an interaction between the factors "capacity ratio" and "fleet configuration" (see Figure 38). When the system has extra capacity the differences in fleet configurations have no impact, but when the system approaches 90% capacity the differences in service level are greater. This interaction is very similar to the interaction between capacity ratio and coefficient of variation. These similarities may suggest that a system operating at low capacity is more robust and assimilates better the changes in demand and loading capacity.

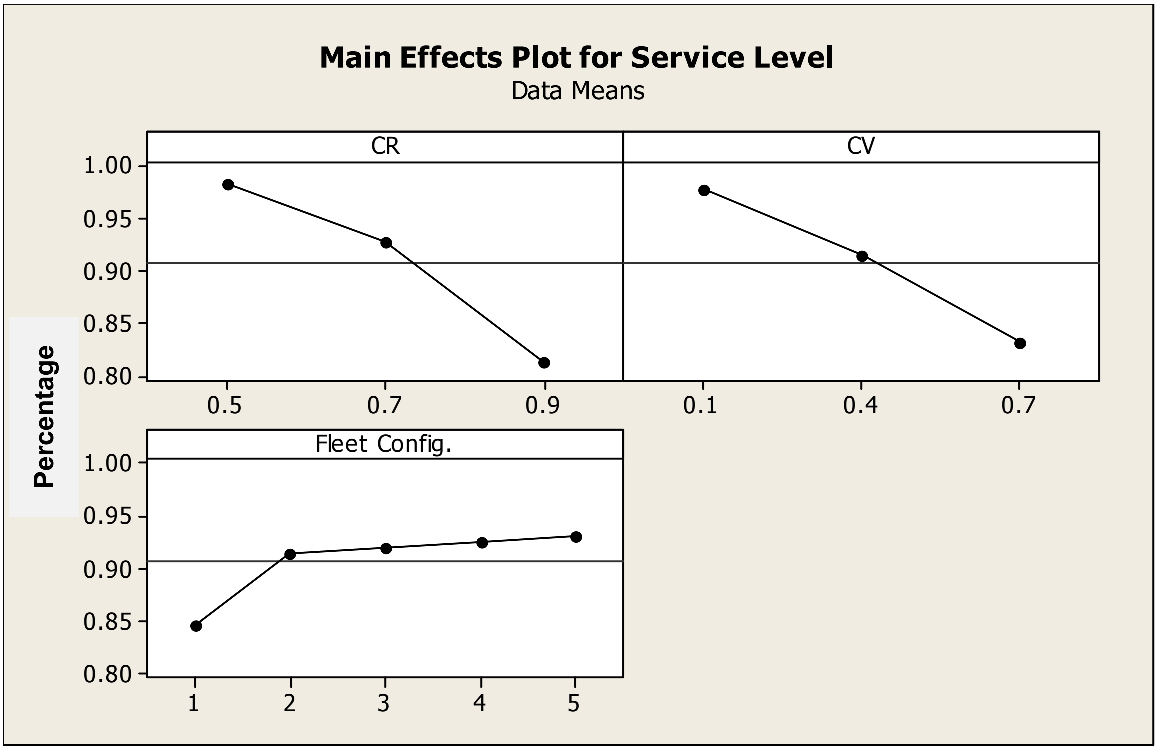

Figure 37. Main Effects Plot for Service Level (Fleet Configuration Experiment)

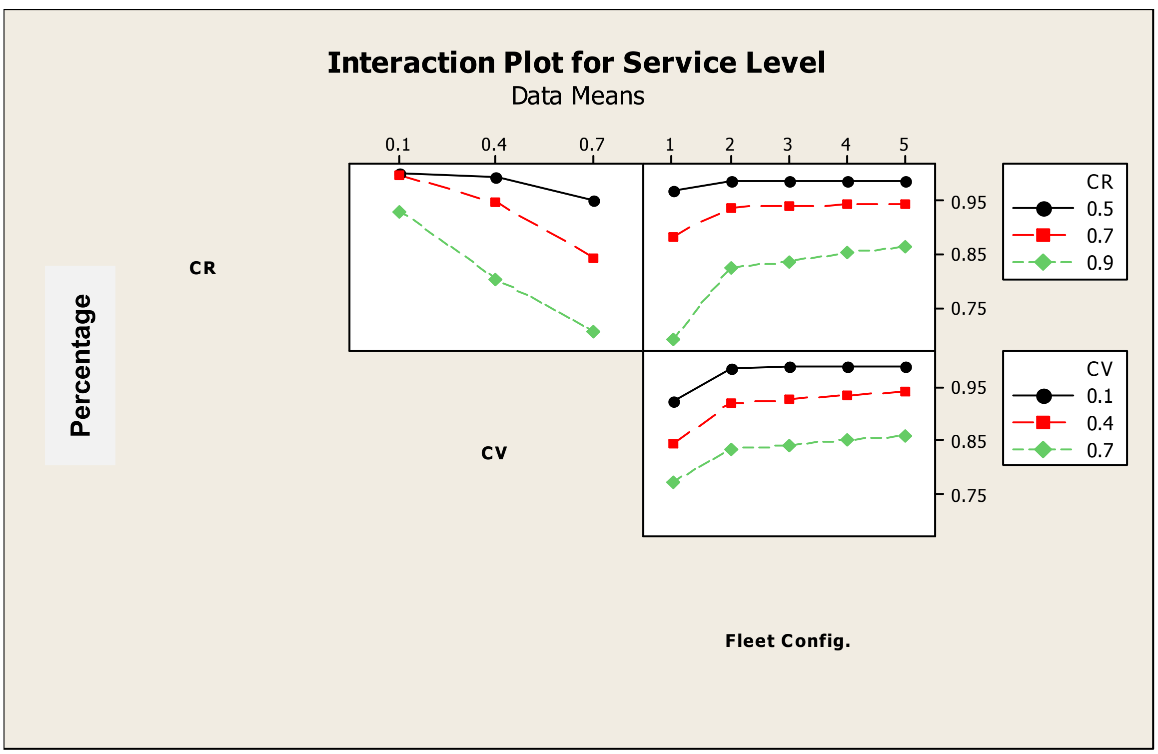

Figure 38. Interaction Plot for Service Level (Fleet Configuration Experiment)

5.5 Response Tradeoffs

Service level is a performance metric that companies track. Figure 39 represents the possible tradeoff that can be seen between service level and carbon emission. Figure 40 represents the possible tradeoff between service level and cost. When graphing the relation between carbon dioxide emissions and cost with service level it can be appreciated that by sacrificing 1.63% in service level (between level B and E) the average saving of carbon dioxide is 24.51 Kg per route and of cost is $10 per route (see Table 25). Furthermore, it can be observed that less than a percentage increase in service level (between level D and E) result in an investment of approximately $6 dollars and additional emissions of 15 CO_2 Kg per route.

Table 25. Response Tradeoffs

Fleet Configuration	Average CO_2/Route (Kg)	Average Cost/Route ($)	Service Level
A	137.28	135.99	84.69%
B	155.81	141.23	91.39%
C	158.68	142.29	91.93%
D	164.45	144.59	92.62%
E	180.33	151.50	93.02%

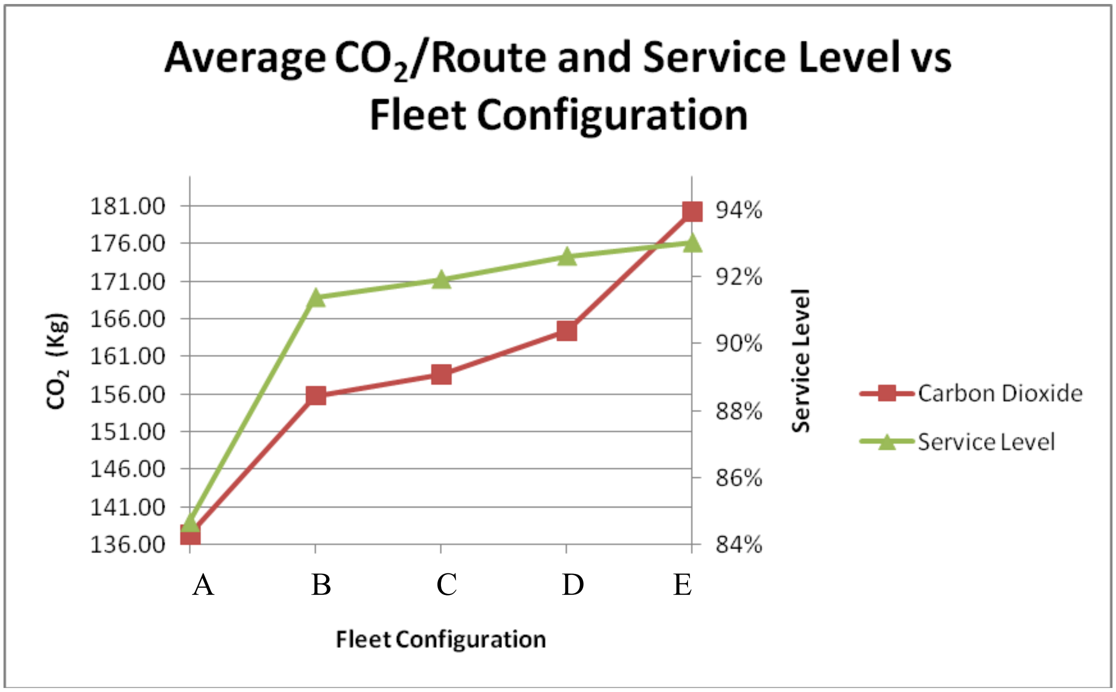

Figure 39. Average CO_2 Emissions per Route and Service Level vs. Fleet Configuration

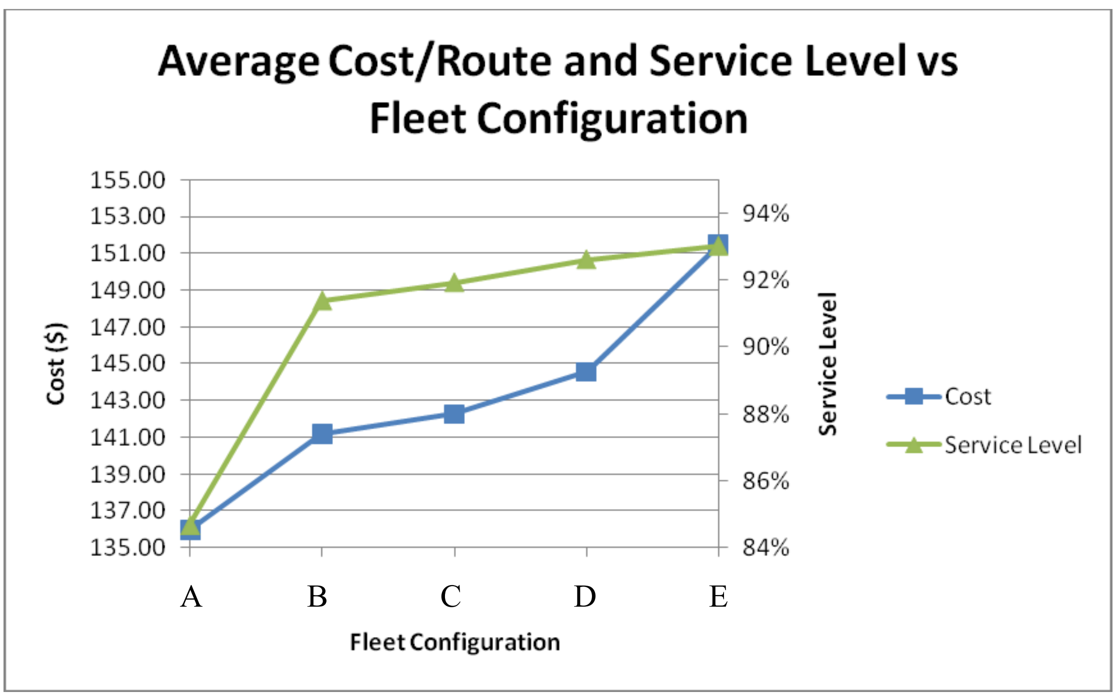

Figure 40. Average Cost per Route and Service Level vs. Fleet Configuration

6. CONCLUSIONS AND FUTURE RESEARCH

6.1 Conclusion

Considering the supply chain design and the assumptions made in this research, the hypothesis that an increase in demand variability results in increased carbon dioxide emissions can not be rejected. In regards to cost and service level in the supply chain, it can be concluded that the increase in variability also results in cost increments in the supply chain and in a reduction of service level.

Analyzing the response of the wholesaler under different capacity levels it can be observed that when the system has significant additional capacity it can better assimilate demand variability decreasing the effect on the responses of carbon dioxide emissions, cost and service level. On the other hand, when the system is close to its maximum capacity it becomes more sensitive to demand variability and the magnitude of the impact increases.

The behaviors of the demand variability and demand ratio are true for different system configurations and fleet configurations. Based on the experiments it can be concluded that the simulation model used may be a tool to represent and analyze different system configurations of the supply chain.

When the same fleet configuration is used it can be concluded that the increase of average number of trips correlates to the increase of carbon dioxide emissions and cost. Under the assumption that trucks with lower loading capacity have a higher fuel efficiency, the truck fleet configuration that had the smaller total loading capacity produces less carbon emissions and cost, but lower service level. On the other hand, a fleet configuration with bigger loading capacity and lower fuel efficiency results in

increased carbon dioxide emissions and cost, but higher service level due to a reduction of the number of trips required to deliver product.

Under the assumptions and definition of the responses used in this research, it can be observed that when different truck fleet configurations are considered there are significant tradeoffs between carbon dioxide emissions and service level and between cost and service level. When the truck configuration with the larger loading capacity is used to distribute the product it results in higher service level but it also results in higher carbon dioxide emissions and cost. When truck fleet configurations with smaller loading capacity are analyzed the reduction observed in service level is not as significant as the savings in carbon dioxide emissions and cost.

Finally under the assumptions of this research the relation between carbon dioxide emissions and cost are positively correlated with the consumption of diesel. The impact on cost may be reduced by a lower price in the gallon of diesel, but the impact on the environment would continue to be the same.

6.2 Future Research

This research can be the starting point for the analysis of supply chains in relation to the production of carbon dioxide emissions due to demand variability. The scope of the research considered a two-stage supply chain and only one transportation mode. Further research, including more echelons of the supply chain as well as different transportation modes can be done in order to quantify the impact of demand variability, comparing the results with the ones concluded in this research. Several assumptions were made that differ from real world conditions, a model that considers factors like variable fuel

consumption based on the changes of product weight due to product delivery and incorporation of fuel consumption while the truck is idle making the deliveries, will make the model more realistic. Additionally, different demand patterns and trends can be analyzed to determine their impact on the supply chain, validating the tool under other scenarios and extending its usability for other types of supply chains.

After determining that the fleet configuration is strongly correlated to the responses, further research is recommended to analyze the optimal fleet configuration using an optimization model, having the goal of reducing carbon dioxide emissions while maintaining constraints like service level. Furthermore, this research uses a very simple assignment method for routes and trucks; research can be done to analyze the economical and environmental impact of different assignment policies used. Following the environmental trends, an analysis including the use of alternatives fuels and their impact on carbon dioxide emissions and cost would add value to the model as a decision making tool.

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APPENDECIES

Appendix A. Wholesaler Raw Data

Route ID	Number of Stops	Demand (cubes)	Distance (miles)	Total time			Total Minutes	Truck Size
				H	M	S		
101	13	826	33.7	5	19	51	320	1650
102	18	904	32.4	5	41	15	341	1650
103	12	726	29.5	5	11	53	312	1650
104	24	754	95.9	9	51	0	591	1000
105	11	662	84.3	6	59	58	420	1000
106	16	502	42.1	6	19	21	379	1350
107	17	528	50.1	6	16	30	377	1000
108	11	831	37.7	5	53	48	354	1350
109	16	667	150.7	8	32	27	512	1350
201	20	1599	33.5	7	23	2	443	1650
202	25	1207	47.6	8	2	36	483	1650
203	23	1651	30.8	7	52	29	472	1650
204	17	1082	154.5	10	33	4	633	1350
205	23	1298	92.4	9	32	22	572	1000
206	24	882	58.9	7	25	15	445	1350
207	19	742	36.9	7	29	41	450	1000
208	22	1160	188.8	12	0	57	721	1350
209	23	1487	191.8	12	15	33	736	1000
210	19	1036	80.3	8	54	18	534	1350
211	16	916	106.7	9	21	54	562	1000
212	18	664	110.1	9	12	43	553	1350
213	16	927	89.3	8	46	14	526	1650
214	15	901	98.5	7	21	47	442	1000
301	24	1631	37.1	7	53	50	474	1650
302	25	1595	105	9	18	16	558	1650
303	20	1349	22.7	6	36	48	397	1650
304	15	648	92.2	7	42	5	462	1350
305	17	913	136.5	9	45	3	585	1000
306	24	821	25.7	7	44	20	464	1350
307	17	889	32.5	6	54	43	415	1000
308	24	1031	119.6	10	40	6	640	1350
309	21	681	60.7	8	16	25	496	1000
310	18	1109	71.8	8	57	51	538	1350
311	21	731	93	8	19	7	499	1000
312	19	583	61.8	7	54	12	474	1350

313	20	1006	96.4	9	18	3	558	1650
314	19	901	46.8	9	41	12	581	1000
315	17	623	39.3	6	35	1	395	1000
401	26	1629	34.6	9	2	15	542	1650
402	25	1463	43.6	9	24	27	564	1350
403	21	1480	32	8	37	54	518	1650
404	19	1064	92	9	15	43	556	1000
405	18	1130	140.1	10	31	38	632	1000
406	22	1052	34.8	7	46	49	467	1650
407	20	720	40.1	6	27	47	388	1650
408	29	941	100.6	10	36	52	637	1350
409	21	728	52.8	7	41	12	461	1350
410	23	1016	93.9	10	10	25	610	1000
411	22	764	199.2	11	55	47	716	1000
412	21	628	103.4	9	16	48	557	1000
413	22	903	137	9	53	4	593	1000
414	18	944	136.2	10	41	20	641	1000
501	21	1506	95.6	10	20	0	620	1650
502	24	1070	36	8	7	4	487	1350
503	28	1573	54.1	10	2	47	603	1650
504	20	819	84.4	8	52	50	533	1000
505	21	719	150.4	11	24	33	685	1000
506	23	719	50.9	7	10	11	430	1650
508	18	863	55	7	23	0	443	1350
509	20	684	83.9	8	15	43	496	1350
510	21	822	59.2	8	0	38	481	1000
511	15	606	184.8	10	59	52	660	1000
512	23	1008	112.4	10	32	43	633	1000
513	17	893	122.4	9	2	15	542	1000
514	12	496	94.2	6	49	45	410	1000

Appendix B. CD Content

The following folders can be found in the CD attached:

Raw Data and Thesis Defense: This folder contains the raw data from the wholesaler used in this research.

Simulation Model 1 System Configuration Low: This folder contains the simulation model, output file and the simulation results used to run the main experiment using the low level of the factor “System Configuration”.

Simulation Model 1 System Configuration High: This folder contains the simulation model, output file and the simulation results used to run the main experiment using the high level of the factor “System Configuration”.

Simulation Model 2 Fleet Configuration: This folder contains the simulation model, output file and the simulation results used to run the second experiment including the factor “Fleet Configuration”.

DOE Model: This folder contains the Design of Experiments of both experiments used in this study.