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Electricity and Fuel Consumption in a Lean Energy Supply Chain

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To the Graduate Council:

I am submitting herewith a dissertation written by Mostafa GhafooriVarzaneh entitled "Electricity and Fuel Consumption in a Lean Energy Supply Chain." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Industrial Engineering.

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Electricity and Fuel Consumption in a Lean Energy Supply Chain

A Dissertation Presented for the

Doctor of Philosophy

Degree

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Mostafa GhafooriVarzaneh

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Dedication

Dedicated to:

My father, who was the most inspiring person in my life and my role model.

My mother, for her love, support and encouragement.

My beloved sisters, Elham and Nafiseh.

My supportive and kind brother Ali.

My beautiful nieces, Sara, Tasnim and Sana.

I also want to dedicate this dissertation to Ailin, for her constant support and encouragement from undergrad to PhD.

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I am also grateful to my committee members, Prof Kobza, Dr. Bell and Dr. Simonton for their guidance and comments on my research.

The completion of this work could not have been possible without the help and support of an excellent team. I want to appreciate the help of Vahid Ganji, Dr. Lance Saunders, Hesam Shams, Ailin Asadinejad, Mohammad Raji, Esdras Araújo, Roshanak Akram, Teron Daering, Benyamin Moradzadeh, Dhanush Agara Mallesh, Abhishek Chimalapati, Kaveri Takur, Girish Upreti, Bharadwaj Venkatesan, Seyyed Ahmad Niknam, Enrique Macias de Anda and my friend Ali Ardakani.

Abstract

Human activities are the main sources of environmental pollution. Awareness about this fact, motivated us to make changes in different paradigms of our lives including industrial or personal activities. Environmental activities assumed to have conflict with financial objectives, in this study we try to align business requirements with environmental concerns.

Among all human activities, generating energy has the most negative impact on the environment. The major part of the generated energy will be consumed in transportation and industrial demand which makes them the most effective targets for the reduction of greenhouse gas emission. In a lean environment, small batch sizes increase the number of set-ups and consequently, energy consumption in manufacturing. On the other hand, small batch sizes increase the delivery rates and complexity of transportation. Therefore, the focus of this study will be on reducing the environmental impact of human activities in transportation and industrial loads as a part of lean supply chain.

The focus in transportation will be on trucking with gasoline or diesel as the source of energy. In industrial loads, the emerging opportunities after deregulation of the electricity market and incentive programs toward cleaner productions encouraged us to focus on electrical demand in the industry.

Despite motivations for reducing emissions in supply chain management, lack of knowledge and expertise in measuring, modeling and optimizing energy consumption is a barrier in production section. In this dissertation, a framework of a power measurement and simulation will be introduced. In the next section, a production planning model incorporating energy will be developed considering different states of electricity consumption (idle, startup, etc.).

As the next segment of the supply chain, a method for optimal carrier selection and routing will be developed and tested based on real world data. This model can use the advantage of geographically distributed carriers while utilizing private fleet at an acceptable level. Based on the insight developed in transportation and industrial loads, an experience based performance measure will be developed to quantify the performance and associated energy consumption in the supply chain.

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1 Introduction and overview

1.1 Motivation of the study

The motivation of this dissertation is to align CO_2 emission by reducing energy consumption in a manufacturing environment with a key focus on electrical demand in manufacturing and fuel consumption in transportation. Environmental motivations can be aligned with business requirements to reduce the cost of providing a product or service in a manner that reduces the CO_2 emission of a supply chain. Energy efficiency collides with emerging opportunities provided by deregulation of the power market, demand response programs and other factors have encouraged researchers to consider a more significant role for energy in designing a manufacturing based supply chains.

This approach is a far cry from energy management viewed only based on the infrastructure, and examples are changing lights or HVAC. This traditional approach has received significant attention in the literature, for the following reasons:

- Rising electricity and energy price [1].
- Deregulation of power market [2].
- Awareness and stewardship of environment and greenhouse gas (GHG) emission [3].
- Reduction of energy supply risk [4].

The recommended approach focuses on reducing electricity consumption in manufacturing by understanding demand, volatility of electricity price and possible improvements in operation. This paradigm looks at manufacturing from a lean perspective, on how to align cost with demand, manufacturing electricity consumption and transportation fuel consumption.

1.1.1 CO_2 emission

CO_2 emission has been considered as an important indicator of environmental pollution. Human activities, including industrial processes, produce greenhouse gasses. Among all the activities, production of energy (generating electricity and providing fuel) is the largest source of GHG emission. Fig. 1.1 shows that the creation of energy itself for societal needs is the most significant generator of GHG [5].

Fig. 1.2 lists the sectors of energy consumption by source, primary and end users [6]. From the total primary electric power produced, a section will be utilized in industry, transportation (like hybrid vehicles), residential and commercial again.

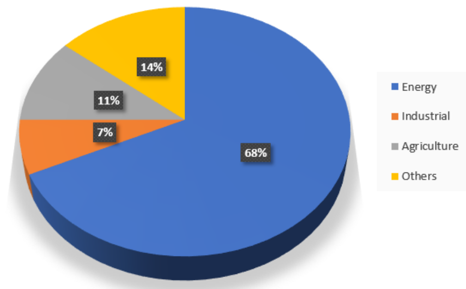


Figure 1.1: Estimated shares of global anthropogenic GHG

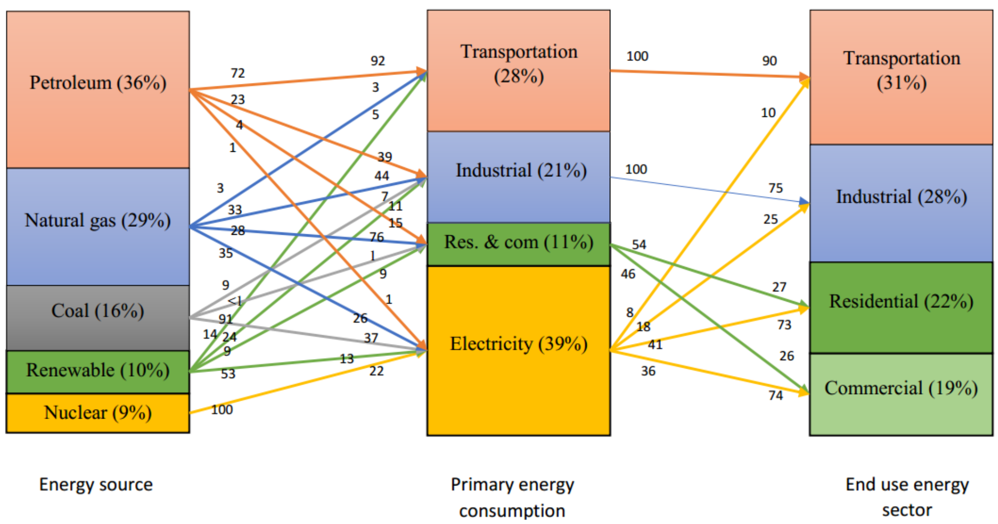


Figure 1.2: US primary energy consumption by source and sector

As illustrated in Fig. 1.2, this energy creation can be decomposed into four sectors of the economy that consume energy. The focus of this research is at the end use energy sector; specifically, the research focuses on addressing transportation and the industrial sector as they represent 59% of total end-use energy consumption and has traditionally been the subject of a lean manufacturing and lean supply chain. A key element in a lean supply chain is to reduce the fuel cost by optimizing the route. Another concern in lean manufacturing is to view electricity consumption as a cost reduction mechanism rather than a fixed production cost. This paradigm shift requires two key components, ability to measure and monitor power consumption as a function of production and capacity to reduce electricity cost based on electricity availability price and production demand.

1.2 Background

1.2.1 Relevance of study

To prove the relevance of the study, we compare US with other countries utilizing GDP, population and pollution data extracted from "Key CO_2 Emission Trends" report [5] and "Trends in Global CO_2 Emissions" [7] and World Bank database [8]. The extracted data has been analyzed using statistical software (NCSS).

The results presented in Fig. 1.3 shows CO_2 emissions generated by different countries. The United States and China are producing a significantly larger amount of pollution in comparison to other countries. An argument might be both the nations have higher GDP and population. Based on this, a political discussion is going on about US's need to reduce its CO_2 emission level.

Based on CO_2 emission, year, population and GDP, the United States and China clustered together. This group (cluster 2) represents the countries with a high amount of CO_2 generation considering population and GDP. Fig. 1.5 illustrate that in last ten years India has joined the large polluter cluster. Fig. 1.4 illustrates that the United States CO_2 emission has been stable during 1990-2014. While shows progress toward a cleaner environment, US is still a high polluter nation. Developing countries such as China and India produce excessive GHG emissions and trends illustrate that emission has not stabilized.

CO_2 vs. population in Fig. 1.5 illustrates that emission in China increased while the population was not increasing significantly. US generates less CO_2 per capita than before, which is another sign of stabilized pollution.

Fig. 1.6 presents changes of CO_2 emission vs GDP over the period of 24 years. US controlled emission in a growing economy while China's CO_2 increased beyond their economic growth.

A multivariate regression model has been developed to estimate the amount of CO_2 emission as a function of year, GDP, and population. This model can predict the CO_2 emission by 93% R-Squared value. This implies that the model can estimate the amount of CO_2 emission with high precision. Residuals have been plotted in Fig. 1.7 which illustrate a sudden increase in residuals, associated with China. A similar increase in residuals (around row 380) is associated with the United States.As discussed so far, US have implemented effective strategies and stabilized CO_2 emission but not sufficient especially if CO_2 emission can be aligned with the cost reduction of production/service.

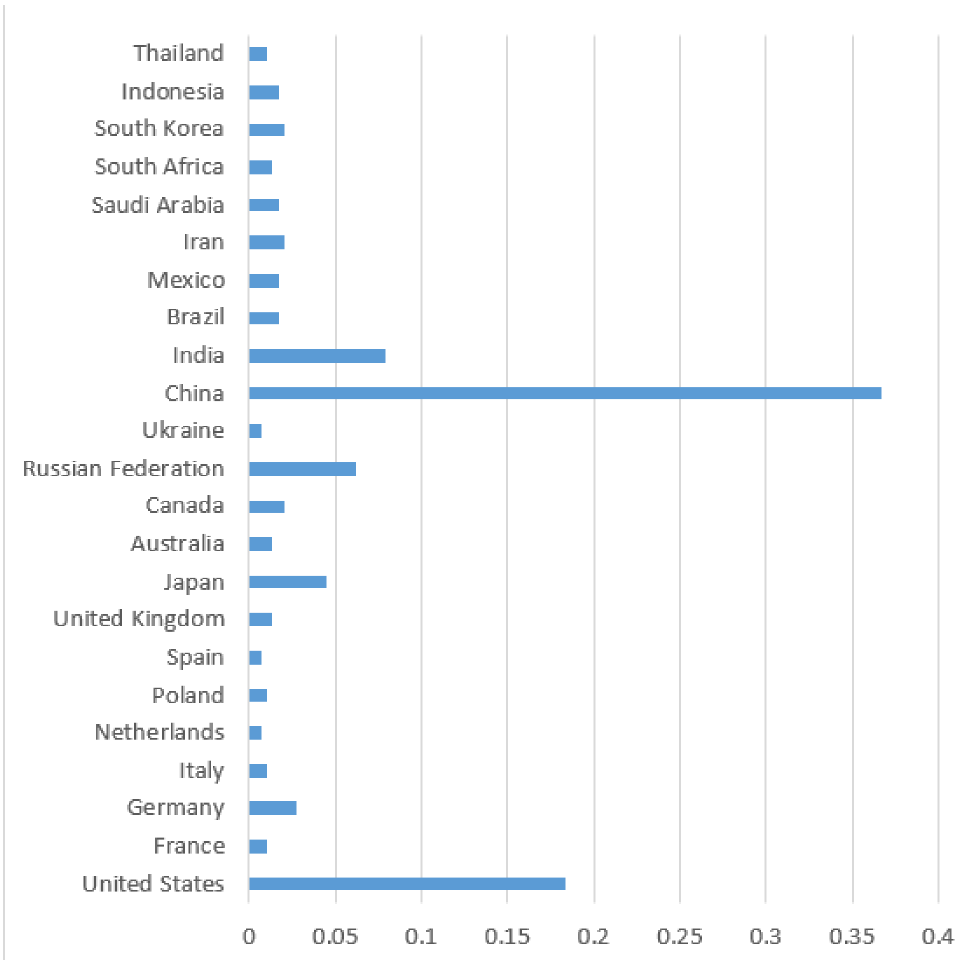


Figure 1.3: CO_2 emission by country

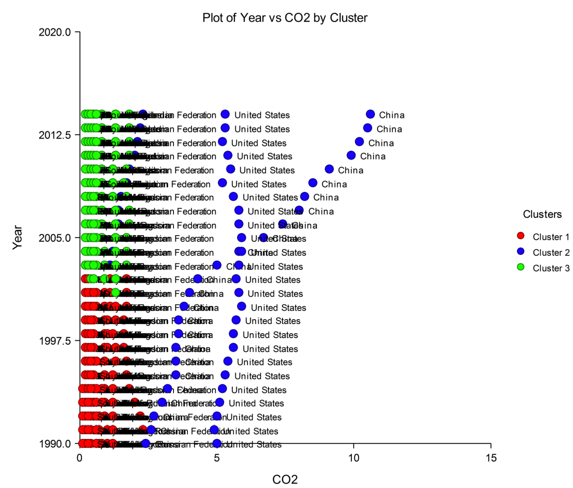


Figure 1.4: CO_2 emission by country by year

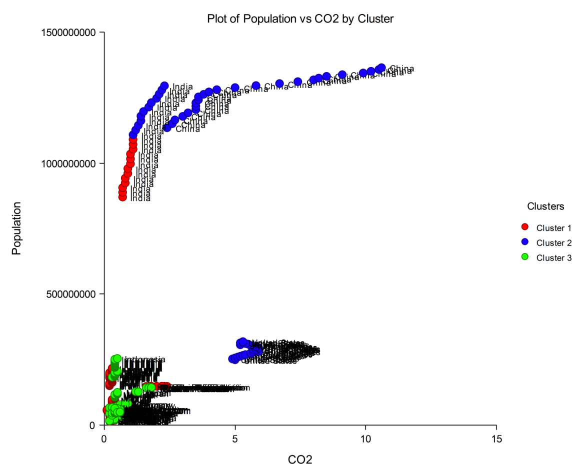


Figure 1.5: $CO_2$by population by country

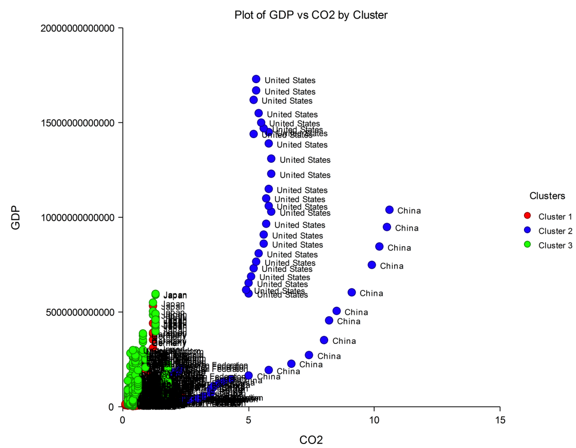


Figure 1.6: CO_2 by GDP by country

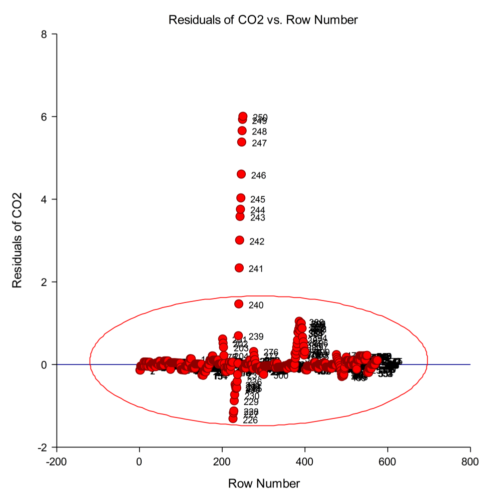


Figure 1.7: Residual by row

This political discussion cannot be resolved unless the cost of production aligns with environmental concerns. This paradigm will be developed in this study with the focus on the United States to create greater competitiveness yet better stewardship of the environment. The research can be duplicated in different countries.

1.3 Problem statement

Successful strategies in the United States stabilized the emission of CO_2 but yet not enough to exclude this country from “high polluter countries” cluster. In the previous section, it was discussed that the effort to reduce GHG emission narrows down to the methods of energy production and energy consumption. Among end-user energy consumption sectors, Fig. 1.2 illustrates the best targets are transportation and industrial sectors. In this study, methods will be introduced to align energy and environmental concerns with financial objects and business requirements.

Manufacturing and transportation are the main parts of a supply chain. Fig. 1.8 illustrates how different parts of a supply chain are connected. Material flows from supplier to customer, and private fleet or outsourced carriers are responsible for moving the material. Fossil fuel is the primary energy source in this section. Studies show that current decision-making approaches in this section resulted in a high amount of empty miles (12.5% - 15.8%) in the United States [9]. A more efficient strategy based on the combination of internal and outsourced carriers has been recommended and the decision-making tools have been developed based on accurate fuel consumption models. This approach not only reduces the cost and facilitates the decision-making process in carrier selection and routing, but also takes advantage of the geographic distribution of outsourced carriers to cut empty miles and save fuel.

Manufacturing or industrial efforts are the heart of a supply chain, analysis of this part requires considering the flow of material from supplier and flow of information (for example order) from the customer. Peter Drucker has the famous quote: "you can’t manage what you can’t measure", consequently a method for energy measurement and simulation has been recommended for machining processes. Then, in order to align energy and business concerns in manufacturing, two production planning models have been recommended to optimize the cost of production considering energy. The line managers will be able to move the production between different hours of one shift or call for an extra shift to save on production and energy cost simultaneously.

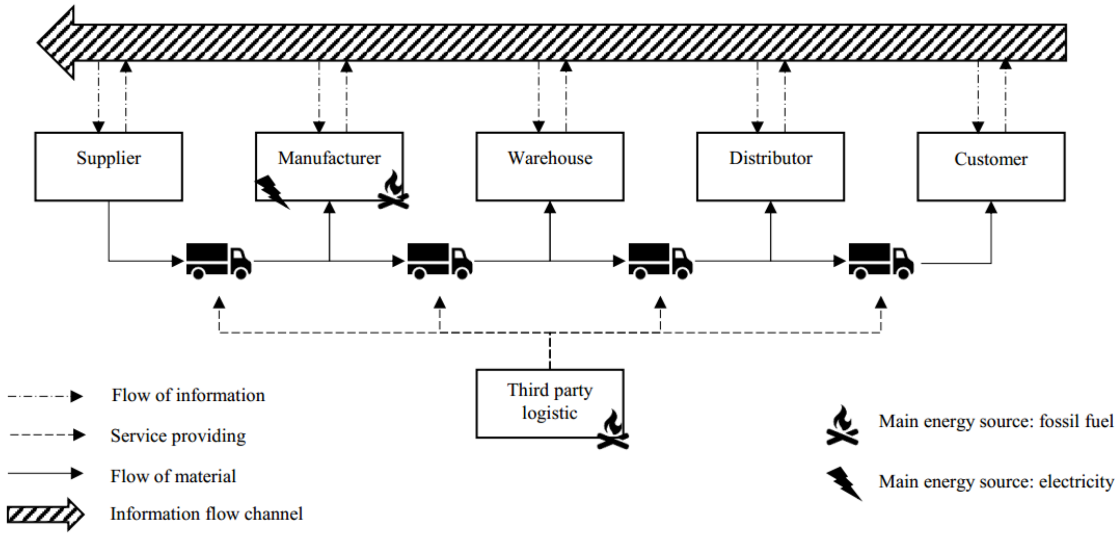


Figure 1.8: Supply chain framework

At the end, analytic groups need to be able to quantify the performance both in traditional and green supply chain frameworks. A method for aligning environmental KPIs with a widely accepted standard for performance measurement will be introduced as the last part.

1.3.1 Energy cost in manufacturing

Small batch size is one of the key aspects of lean manufacturing. The more complex sequence of products in a lean production compared to traditional manufacturing will cause more set-up and start-ups. Motors as the primary part of manufacturing devices consume more energy during start-up. Here the dilemma of lean and green manufacturing arises where there should be a balance between the number of start-ups and batch size to save energy in the lean environment.

Petroleum, Natural gas, coal, and electricity are being consumed in the industrial sector and while the competition becomes closer in the industry all of the energy sources show an increasing trend in price [6, 8]. Despite natural gas, coal, and petroleum, the price of electricity changes hourly in a deregulated power market which provides more saving opportunity and motivation for line managers to consider it in production planning. On the other side, due to many incentives and subsidies, industries are going toward using cleaner energies like electricity instead of fossil fuels [10]. Consequently, energy and more specifically electricity price in manufacturing will be an inevitable part of a lean supply chain.

Electricity consumption in the production line can be divided into different states including start up, idle, working, etc. Energy consumption is a function of both time and state.

1.3.2 Energy cost in transportation

Transportation is considered as a waste in a lean environment. On the other hand, small batch sizes will cause more available products and more frequent and complex delivery.

World Bank database shows an increasing trend both in fuel consumption and diesel price worldwide [8]. Russel *et al*. also emphasized the impact of fuel price as a game changer in the supply chain. The volatility and increasing trend in fuel price shifted the focus from storage cost to delivery and shipment costs [11]. The volatility also encouraged third-party carriers to consider fuel cost based on daily average price in their contracts and shift the risk toward the distributor/manufacturer company.

Different factors can contribute to fuel cost, Suzuki recommended a fuel consumption model based on route length, payload weight and gradient of the road [12].

1.4 Structure of dissertation

The remainder of the dissertation is structured as follows.

Chapter 2 This chapter introduces a framework for data collection, simulation, and visualization of energy consumption with the goal of reducing energy consumption by balancing idle time and number of start-ups. Data collection is generally the most time-consuming part of each simulation project. This step becomes even harder when one wants to consider energy in the model. On the other hand, most of the production managers and industrial engineers do not have enough knowledge about energy and cannot measure and simulate electricity consumption. In this chapter, a method for data collection and simulation of energy will be introduced that does not require academic knowledge about electrical engineering. The primary focus is on motor loads which are the most common sources of energy usage in an industrial sector. A MATLAB toolbox also created to support energy simulation in *SimEvent*.

Chapter 3 After being able to measure and simulate energy consumption, the next step is to develop a production scheduling model based on production constraints as well as energy cost to be able to take advantage of electricity price variations. In the recommended optimization model different order arrival scenarios have been considered as the input to the supply chain. Other variables such as production time, startup time, setup time, product mix, and other factors formed a complete and resilient model. Then the model has been tested in a Real Time Pricing market where the electricity price changes hourly. In the end, a Design of Experiment approach was employed to examine the effect of each variable in reaction to the price volatility in the electricity market. Based on this step, a distribution for electrical load change has been obtained.

Chapter 4 After manufacturing the product, it is time for distribution and delivery. In this chapter, the opportunity of using a combination of private/dedicated trucks or global carriers has been investigated. Based on a new cost structure, a single objective exact algorithm for minimizing the variable cost of travels introduced. The variable cost of trip includes maintenance fee, salary, fuel, etc. In this combined strategy, by taking advantage of employing the closest common carrier to the pickup and delivery points, travel costs and fuel consumption will be reduced, and less GHG emissions will be generated while the quality of service is maintained.

Chapter 5 In chapter 5 the last part of the supply chain will be considered which is the flow of information. In this chapter environmental KPIs will be added to the current KPIs in the company. Every company has a set of KPIs developed based on years of experience and dealing with specific conditions and customers. A text analysis method is introduced to utilize the expertise of the company in addition to widely employed SCOR model and green manufacturing criteria.

The general framework of the dissertation can be described as Tab. 1.1.

Table 1.1: Dissertation structure mapped on supply chain

	Manufacturer	Transportation	Distribution	Customer
Energy source	Electricity	Fuel	Electricity	N.A.

Variable assessed	Production scheduling
	• Reducing electricity consumption via balancing set ups and start-ups (chapter 2)
	  – Energy consumption
	• Discounted electricity price (chapter 3)
	  – Arrival
	    ∗ Arrival rate
	    ∗ Product mix
	  – Process
	    ∗ Process time
	    ∗ Throughput
	    ∗ Disruption
	      · Set-up time
	      · Start-up time
	  – Arrival
	    ∗ Direct energy
	    ∗ Indirect energy
		Chapter 4
		• Road transportation cost
		  – Internal/partnered fleet cost
		    ∗ Fixed cost
		      · Overhead cost
		    ∗ Travel cost
		      · Fuel cost
		      · Salary
		      · Maintenance cost
		  – Outsourced/global carrier
		• Business requirements		

Outcome	• Chapter 2: Visualization of energy consumption in scheduled production
	• Chapter 3: Mathematical model for scheduling production considering energy
		• Chapter 4
		  – Carrier selection
		  – Optimal routing
		  – Fast method to solve VRP		

Green KPIs (Chapter 5)	• Energy consumption and states • Shifted load • Saved energy cost	• Fuel consumption • Traveled miles • Empty miles		

2 Conceptual Framework to Reduce Electricity Consumption of Manufacturing Equipment

2.1 Abstract

In this chapter, we focus on set-ups in a lean environment as seen from energy consumption perspective. We try to consider various electrical motors and connect their start-up currents to a high rate of set-up changes in lean manufacturing. The conceptual framework for finding a relationship between energy consumption in different states of various machines and production schedule will be demonstrated in this chapter.

This conceptual framework lays a foundation for economic analysis of industrial devices taking energy into consideration. The data collection and modeling is based on regression methods and does not require academic knowledge about electrical engineering which made the data collection simple and straight forward. Based on the recommended framework energy efficiency improvement can be tested and economically analyzed in every scenario. A toolbox based on the structure has been created to simulate energy consumption in the production line and can be considered as an expansion block to SimEvents toolbox in MATLAB. The simulation toolbox also can help schedulers to balance energy consumption with the number of set-up changes in manufacturing.

2.2 Introduction

2.2.1 Scope of the chapter

The key primary consumer of electricity in manufacturing equipment is its motor. In most of the equipment, with different names and application, a motor is playing the central role and in some devices, more than one motor are utilized. Application of motors in wind blowers, pumps, machining tools, and ... shows the variety of roles that motors play in industrial facilities. In EU motors consume 65% of electrical energy and in the US this number rises to 75% and up to 80% in Canada [13].

Generally, in manufacturing equipment, the following types of motors are being used the most:

- Induction motors
  - Single phase
  - Three phase
- Synchronous motors

Table 2.1: Energy consumption in motors

State	Energy consumption in unit of time	Total energy consumption
start-up	$E_{st} \approx (3\,to\,7) * X$	$E_{st} * (\#\,of\,starts) * (start\,duration)$
Working	$E_w = X$	$E_w * (\#\,of\,parts) * (cycle\,time)$
Idle	$E_{id} \approx \frac{X}{10}$	$E_{id} * idle\,time$

– Permanent magnet

In this study, we will look at these various types of motors to find the opportunities in energy saving. Three different states can be considered for power consumption in a motor: start-up, idle and working. Tab. 2.2.1 shows how different states of energy consumption in a motor contribute to the final energy consumption of machine. As it shown in Tab. 2.2.1, energy consumption in working state is a function of number of parts and cycle time. Therefore, the electrical demand in the working state can not be reduced unless a different machine with different E_w purchased. On the other side, energy consumption during idle times and start-up can be reduced by shutting down the machine and reducing the number of start-ups and set-ups.

During start-up, motors consume more energy, and here the conflict of lean and green manufacturing arises. Production planners in a lean environment, try to have small lot sizes which require more set-ups and consequently, more start-ups on motors and therefore a higher energy consumption. So in this chapter and next one, we are trying to introduce approaches to measuring the energy consumption and create a relationship between different states of energy consumption, time and scheduling.

2.2.2 Related literature

Energy management in production lines was a concern for many years, but in recent years, this topic received higher attention in literature and industry. The main reasons can be categorized as following:

- Awareness about the environment, greenhouse gasses, etc. [3].
- Deregulation of power market [2].
- Rising electricity and energy prices [14].

- The competitive market which makes the energy part considerable [1].

- Natural disasters like Japan earthquake, which made some source of energy unavailable [4].

Energy conservation methods have been developed, and most of them are not complicated. Besides, powerful simulation software has been developed and widely used in measurement, strategic planning, optimization however, the lack of a user friendly tool to calculate estimated energy consumption, energy saving and break-even point might be a deterrent factor in energy planning and conservation. In this chapter, a simulation tool and framework is recommended in order to consider energy consumption in machining and production facilities. Generally, energy saving strategies can be categorized into two main areas:

- Improvement of facilities and devices: in this case, total energy consumption will be reduced by changing tools and using more efficient devices

- Improvement of processes: this strategy will change energy consumption via production scheduling/planning.

Energy analysis can be performed via a variety of approaches like visualization/monitoring, simulation, OR modeling, and etc. In addition to diverse approaches—because all the energy parts are not contributing directly to production—various studies reported different ideas and assumptions about categorizing total power consumption. In general, a significant portion of energy consumption is associated with indirect production like start-up and maintenance processes (coolant, oil pressure, etc.). Although the percentage is not the same for different technologies, but as enlightenment, in automotive manufacturing, actual machining consumes only 14.8% of total energy consumption [15, 16]. Solding and Thollander (2006) also considered activates like ventilation, lighting, space heating as supporting processes [14]. Skoogh et al. (2012) considered more states: busy state (product is loaded), idle state (the machine is starving or blocked), down state (failure), standby state (low energy consumption mode) [17]. Cannata et al. (2009) recommended a cross-layer infrastructure for production control. Four states of energy consumption considered in their study: activation mode, idle mode, set-up mode, and operation mode [3]. The objective of Hibino et al. (2012) was to reduce the energy consumption per unit of product. Starting state, idle state, producing state, stopping state, and aborting state (representing failure) have been considered in this study [18]. Seow et al. (2011) considered two general energy states: direct and indirect energy; they referred to environmental energy as indirect energy [19]. Direct energy is divided into theoretical energy and auxiliary energy. Theoretical energy can be calculated based on volume or weight of processed material and total energy consumed. Indirect energy is total energy of each zone divided by the number of processed items. Arena™ simulation software has been utilized in their study. Some researchers focused on one particular device or one part of the production, Liu et al. (2011) focused on painting process in automotive manufacturing [1]. Total energy has been divided into two parts: energy consumption by production process and building energy consumption (HVAC, lighting, ...). For building energy consumption *EnergyPlus* have been used. Meike et al. (2012) concentrated on industrial robots in automotive industry, explained the structure and permanent magnet machines and drive system.

Visualizing and monitoring can provide a better sense about conservation opportunities [20]. Behrendt et al. (2012) introduced energy monitoring procedures and surveyed 232 machine tools with three size categories [21]. Power demand has been analyzed in idle mode and working mode with different rates. Machining power in various states analyzed measured and reported. Sensor network has been recommended to measure the amount of electricity and steam and visualizing the basic unit for energy [22]. Different operational conditions can be visualized and monitored, like normal energy and stopped condition, performance decrement condition, idling or tact delay, and defective condition [4].

The recommended tool in this study provides a visual sense of different states of energy consumption through simulation. Moreover, the data collection for this tool is very simple while effective which can be easily utilized by industrial engineers.

2.2.3 Toolbox specifications

Based on reviewed papers, the following energy states can be considered in every energy modeling project:

- Direct Energy
- Supporting Activities Energy Consumption
- Reducible States
  - start-up
- Wasted Energy

  - Idle mode
  - Standby
  - Failed condition

- Environment Energy Consumption
  - Light
  - HVAC

Depending on the objectives and applications of the study, some of the states can be excluded. For instance in some cases failed condition is not a point of interest, or there is no energy consumption in that state. Environmental energy consumption has its complications and commercial software can handle that, so in this study, HVAC is not considered. The framework introduced in this paper applies to all type of consumption, but as the first step to this research, the main focus will be on motor consumption and ohmic (constant) loads based on the reasons discussed later in the paper. The reader is encouraged to apply the introduced regression-based method to other loads and applications.

2.3 Simulation toolbox development

A major fraction of energy consumption in an industry is consist of electrical motors. In most of the industries—with different names and application—a motor is playing the central role and in some devices, more than one motor are utilized. Application of motors in wind blowers, pumps, machining tools shows the variety of roles that motors play in industrial facilities. In the EU motors consume 65% of electrical energy and in the US this number rises to 75% and up to 80% in Canada [23]. Based on the facts, motors are the most important parts in energy consumption modeling, and there should be a tool to give a visual sense as well as modeling and simulation capability. Modeling motors in software like MATLAB, PSCAD, etc. need so many parameters which are not familiar to industrial engineers and production managers. Without accurate parameters modeling start-up, working mode and idle mode will not be authentic. Data collection requires a considerable amount of time even in normal cases and requiring specific motor parameters will increase the data collection time considerably. In this paper, a compromised method for modeling industrial motors have been introduced. Recommended toolbox does not need detail data for motors and other devices, and it does not require knowledge of electrical engineering.

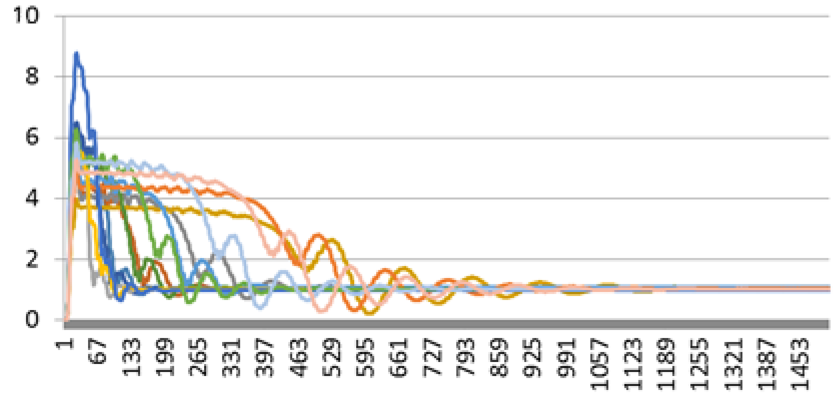


Figure 2.1: start-up current of motors (per-unit)

2.4 Motor start-up modeling

During start-up, motors consume more energy, and this amount can rise to 8 times of full load. Consequently, start-up energy has to be considered in motor modeling. For some type, different motors have been modeled and analyzed with mathematical and statistical techniques.

2.4.1 start-up energy for 3 phase induction motors

Fourteen types of induction motors have been considered and start-up data has been collected for all motors in per-unit format. Fig. 2.1 shows the start-up current versus time for these motors. Regression methods have been used to obtain the best model which fits all the simulated motors. This lead to an order 2 exponential estimator. As shown in Fig. 2.2, the R-squared criteria show the regression model explains 90% of variations in data. There are some dynamic variations that remain unexplained which are not a point of interest in energy management applications.

Generally, order 2 exponential equation can be described as:

$$a * e^{b*t} + c * e^{d*t} \tag{2.1}$$

Since most of the applications care more about total energy consumption during start-up, the integral of the area under start-up current and order 2 exponential estimator has been

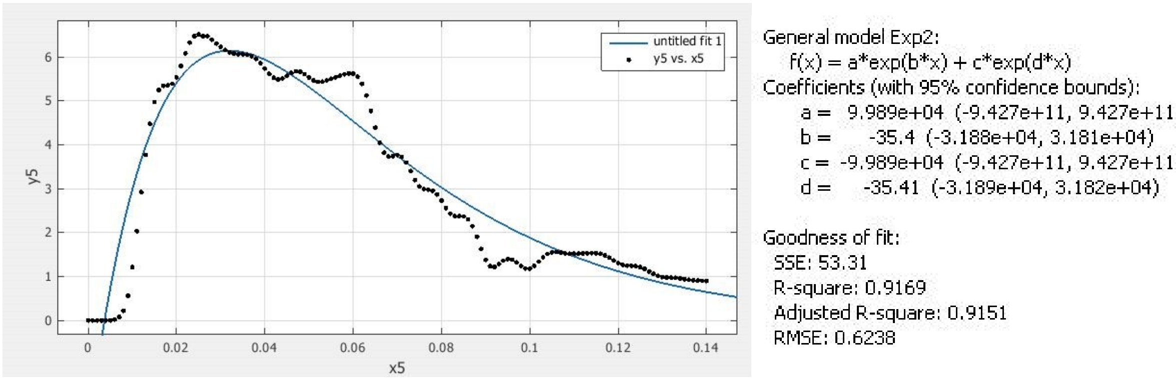


Figure 2.2: Regression model for 3 phase induction motor

compared which show 92% of accuracy.

2.4.2 Single phase motors

Single-phase induction motors are largely used in low power applications and where 3 phase power is not available. Following starting methods are commonly used:

- Split-phase windings
- Capacitor-type windings
- Shaded stator poles

As illustrated in Fig. 2.3 it is possible to consider the starting current as a constant current for all starting methods. The constant start current and time will be obtained from energy audit.

2.4.3 Permanent magnet synchronous motor

Fourteen different PM synchronous motor have been simulated and analyzed. Regression analysis of this type of motors shows that start-up current can be described by an order 2 exponential model with the least R-square of 95% for all motors.

2.4.4 Finding model parameters

For single phase motors the job is not complicated but for 3 phase induction and permanent magnet synchronous motors complications arises. The introduced method in this section is

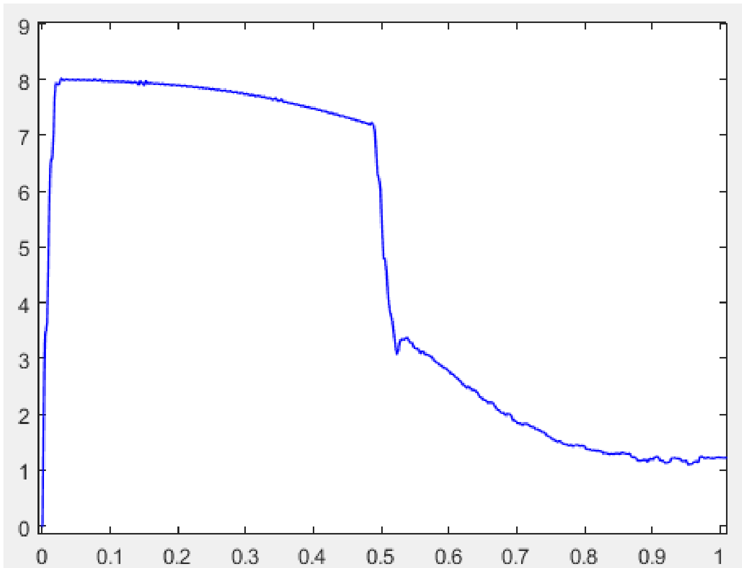


Figure 2.3: start-up current for single phase motor

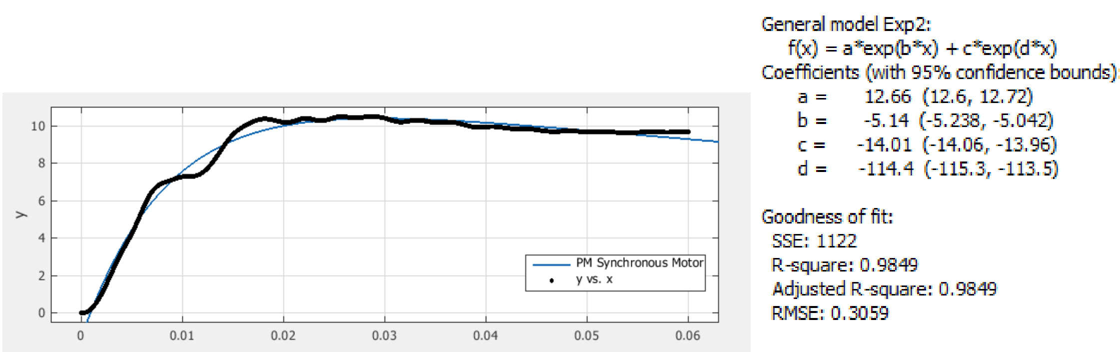


Figure 2.4: Regression model for permanent magnet synchronous motor

rooted in the least square estimation of nonlinear regression models. The main advantage compared to other regression models is that not all the point has been considered in the model because of physics of the problem and prior knowledge which discussed above (equation 2.1). This simplification makes the data collection easier and less expensive. As is illustrated in Fig. 2.5 there are 2 points on the diagram that can help finding the regression parameters. In addition to those numbers, at the start point, current and time are zero, which has been considered in the model. The followings are the points needed for the toolbox:

- Maximum point: for the maximum point of current the following data should be collected
  - I_{max}: the amount of maximum current
  - t_{max}: the time that maximum current occur
- Settle point: after variations and transients, finally the current will go to steady state. This point is called settle point and the following data are needed for the model
  - I_{settle}: steady state current
  - t_{settle}: the point of time that the current stops major fluctuations

After some math operation, the objective function of the least square estimation is as follows:

$$\begin{gathered} f = (a+c)^2 + (I_{max} - a * e^{b*t_{max}} - c * e^{d*t_{max}})^2 + \\ (I_{settle} - a * e^{b*t_{settle}} - c * e^{d*t_{settle}})^2 + \left(t_{max} - \frac{log(a*b) - log(-c*d)}{d-b}\right)^2 \end{gathered} \tag{2.2}$$

The first term derived from start time condition which tries to make the current at time zero as small as possible. The second term and third term are obtained from the maximum point and the settle point. The last term is calculated from first order derivative that makes sure the time of the maximum current in the model is not far from real maximum time. In order to solve the model Newton direction with Goldestein step length has been utilized. Fig. 2.6 illustrates how the optimization model finds the regression parameters very fast and in a few iterations.

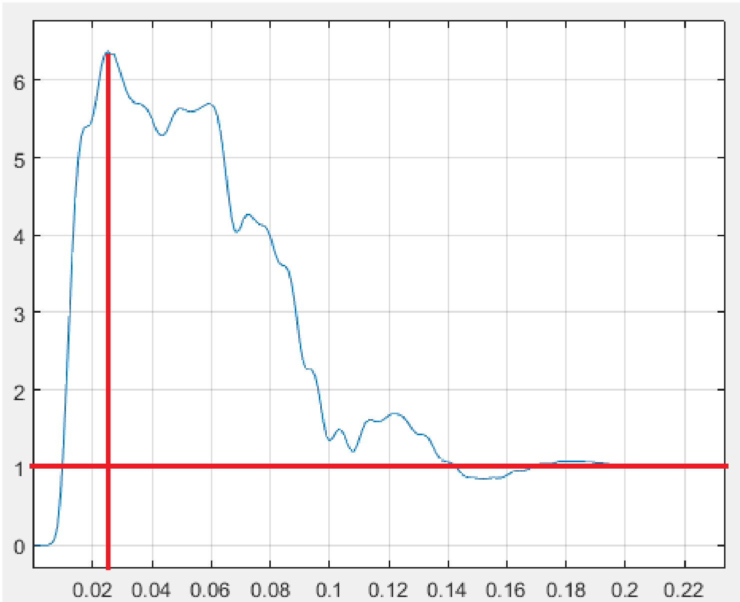


Figure 2.5: Measurement points

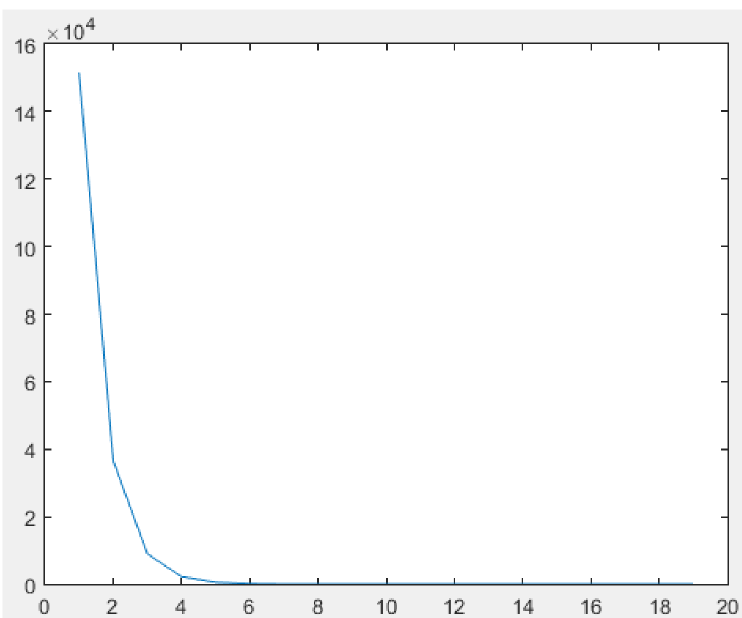


Figure 2.6: Objective function value vs iteration

2.5 Other energy states

Other energy states (Idle, working, etc.) are not complicated to find and most of the industries are collecting those data. In idle mode most of the support activities are not working, the operator needs to leave the machine running idle and consider the minimum energy consumed. It is important to run the machine long enough to make sure all the transients and supporting activities are gone. For working mode, the machine has to start processing a part and the minimum amount of energy consumption should be considered in order to exclude supporting activities energy. The rest of the energy consumption is related to supporting activities which mostly occur periodically.

2.6 Result

The decision we are dealing with in this chapter is whether to turn the machine off during idle times or keep it running to avoid higher energy consumption of start-ups. Assuming that supporting activities does not consume power during idle time, the decision making is straightforward. If the following condition holds the machine should turn off:

$$E_{id} * idle\,time \geq E_{st} * (start\,duration) \tag{2.3}$$

A MATLAB simulation module has been created. This block can be used as a supplement of SimEvents. SimEvents is a MATLAB Simulink toolbox for simulating industrial processes. The introduced block can be connected to SimEvents modules and calculate the power based on selected items on the menu.

Table 2.2: Example 2 parameters

Param.	Value	Param.	Value
I_{max}	4.8 per-unit	I_{aux1}	0.08 per-unit
t_{max}	0.15 min	dur_{aux1}	0.1 min
I_{settle}	1 per-unit	per_{aux1}	1 min
t_{settle}	0.5 min	$Cycle\_t$	3 min

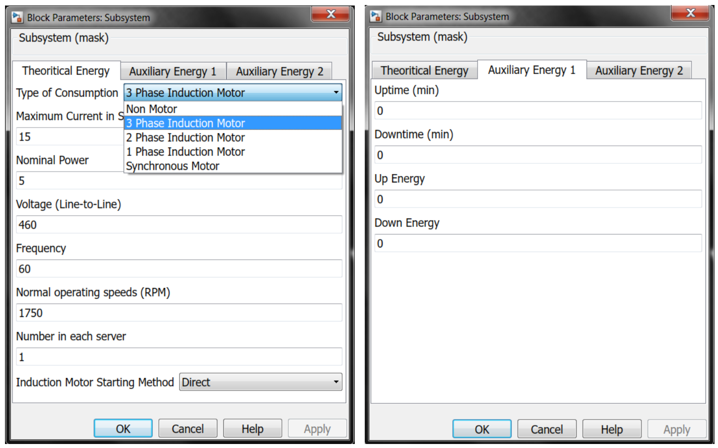


Figure 2.7: Energy simulation block snapshots

A simple simulation model has been developed as an example. The main energy block is highlighted in Fig. 2.8. In the model, there is a “State” signal which indicates that the device should turn off or remain idle when no part is in the machine. The device remains idle if the state signal is 1 and turns off if the signal is 0. The user has the flexibility of trying more complex signal and controls on the device. During start-up and off period, the machine cannot process any item so “Gate” signal disables the device during start-up and downtime. The model can handle energy consumption associated with the supporting activities. In the example, the power consumption of supporting activities are considered to be constant. Electrical current is shown in Fig. 2.9, the user can take advantage of the visualization to understand the effect of start-up, off period, supporting activities use the visual information to make more decision. In the case study, since the start-up time is small, it is better to turn off the machine and avoid running idle.

As another example with characteristics described in Tab. 2.2, assuming 5 minutes between the arrival of parts keeping the device idle instead of turning on and off will save us 11.7% in total energy consumption.

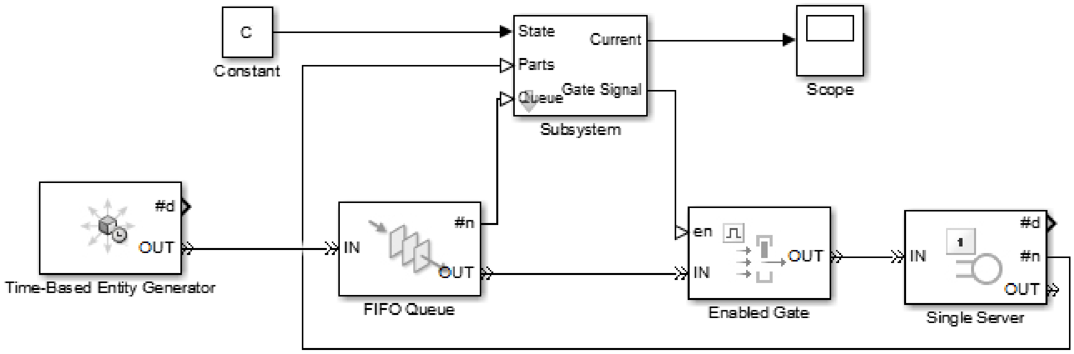


Figure 2.8: Simulink model

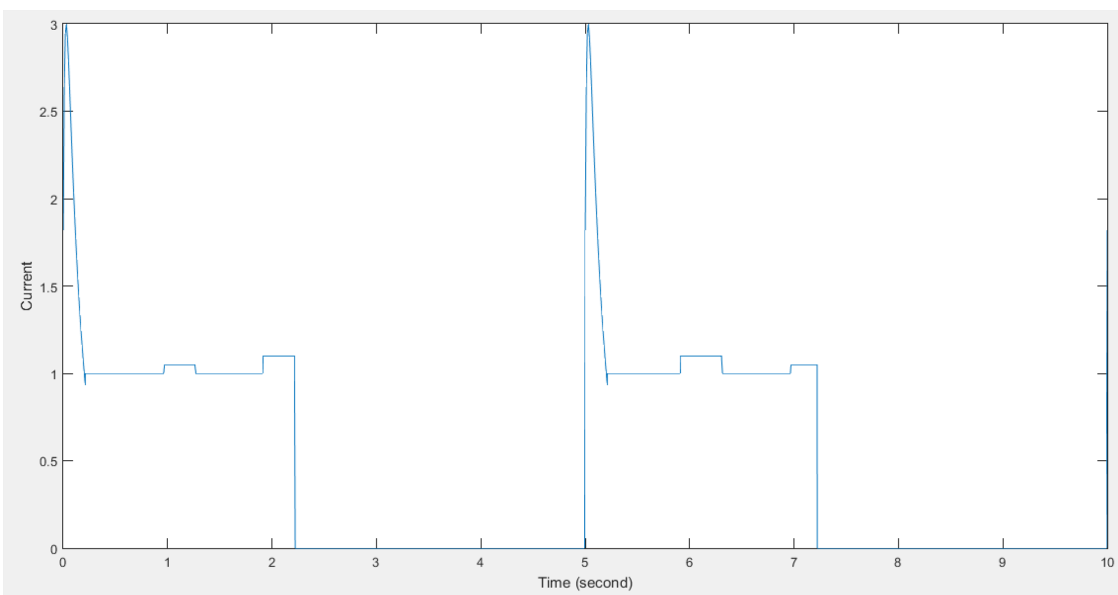


Figure 2.9: Current (Amp)

2.7 Conclusion

In a lean environment, the tendency toward small lot size results in high rate of set-up changes in the production line. The set-up itself will result in either full or partial line start-up. The energy consumption during start-up has been neglected from lot sizing formulation in lean literature. The start-up current of motors—as the primary element of manufacturing—can rise to 8 times of normal consumption. This fact shows the importance of considering energy cost and consumption of start-up in lot-sizing. The analysis indicates that unit one lot size can increase the energy consumption even higher than 10%.

The result of this chapter demonstrates the need to reconsider the basic assumptions of lean manufacturing since the essential element of lean, as lot sizing, increases the energy consumption.

3 Electrical Load Modification in Industrial Demand

3.1 Abstract

In a lean environment, small lot size will result in more frequent set-up changes. As concluded in chapter 2, this additional need for scheduling small lot sizes of multiple products per day results in increased electricity cost, even though Start-up electricity consumption can be minimized. Chapter 3 enhances our ability to minimize the electricity cost impact by considering electricity discount rates.

In deregulated electricity market, discount programs, as well as time-dependent pricing strategies has been implemented. In this chapter, a production planning model will be developed to take advantage of discounted electricity price in an electricity market. The recommended model considers traditional scheduling requirements (such as job sequencing, meeting demand, on time delivery, and ...) as well as energy consumption elements (like Start-up, idle and working energy).

Companies also need to be able to estimate their potential for participating in demand response programs, in order to choose the best demand response program contract. Estimating distribution of load change in response to demand management programs has been targeted in many researches, mostly based on economic and business sale-price models. In this chapter, a bottom-up analysis approach will be considered. As the first step, consumer's decision-making process has been approximated using mathematical modeling. In this step, a novel optimization model for production scheduling has been introduced which takes into account different energy consumption states. In the second phase, a design of experiment (DOE) model was developed based on various energy and production factors. In the third step, two new distributions were introduced based on a variable selected in DOE analysis. The proposed model and approach can be employed in different energy management programs especially machining processes.

3.2 Introduction

3.2.1 Scope of the chapter

In lean manufacturing, demand will be produced in smaller lot sizes. Small lot sizes will result in higher frequency of set-up changes, and as concluded in chapter 2, high rate of start-ups can lead to increased electricity consumption. As discussed previously, three energy consumption states can be considered in the model:

Table 3.1: Nomenclature

Sets and indices	
i	Product type index
t	Time index
Production parameters	
cp_i	Production cost for type i
ep_i	Energy consumption for producing type i
cq_i	Cost of storing type$i$ for 1 hour
p_{it}	Number of items produced from type i at time t
q_{it}	Number of items of type i stored in time t
StC	Start-up cost
TU_i	Process time of one item of type i
sc_i	set-up cost for type i
st_i	set-up time for type i
$idle_t$	Idle time in period t
RD_t	Real demand at period t
SD_t	Shifted demand at period t
Energy Parameters	
C_t	Electricity cost at time t
eq_i	Energy consumption of storing type$i$ for 1 hour
StE	Start-up energy
se_i	set-up energy for type i
iE	Idle energy
Decision Variables	
$v_t = \begin{cases} 1 & \text{if the line started at time } t \\ 0 & \text{otherwise} \end{cases}$	
$psu_{it} = \begin{cases} 1 & \text{if any items of type i has been produced in time } t \\ 0 & \text{otherwise} \end{cases}$	
$nsu_{it} = \begin{cases} 1 & \text{if there is no new setup needed for producing type } i \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$	

- Start-up energy: as discussed in the previous chapter, during start-up motors consume more power. A simple measurement approach has been recommended as well. Even if the start-up energy is not higher than working consumption (like furnace warm up), it can be considered as waste in a lean paradigm.
- Working energy: the power consumption while the machine is processing the items. Ideally, this energy is close to the nominal power of device although the more accurate measurement approach has been described in the previous chapter.
- Idle energy: when the machine is not processing the items, but it is still on, a smaller amount of energy will be consumed compared to start-up and working. Based on chapter 2, production managers will be able to measure this state of energy consumption.

Other than the three listed consumption, the following can be considered in the model:

- Set-up energy: during set-up, different devices like a hand drill can be used. The power consumption of activities related to changing set-up will be considered in set-up energy. The line has been approximated by a single machine, the partial or full start-up energy required after set-up is also considered in this section.
- Storage energy: the over-produced items need to be stored to fulfill future demand. The energy consumption during storage (controlling temperature, humidity, and ...) will be considered in this state.

Based on definitions, it can be concluded that power consumption has a close relation with job sequence and scheduling. In this chapter, an advanced planning approach will be recommended to take advantage of discounted electricity price in an electricity market. Fig. 3.1 describes the framework of a lean energy production with significant parameters and variables. We are going to test the model in two conditions. First, we consider optimal scheduling within a 8 hours shifts to plan the demand considering variations in electricity price within the shift. However, there is a significant difference between the average of electricity price in the first shift and second shift. The second model tries to concurrently optimize the cost of production and electricity, considering a higher cost of labor and lower cost of electricity in the second shift.

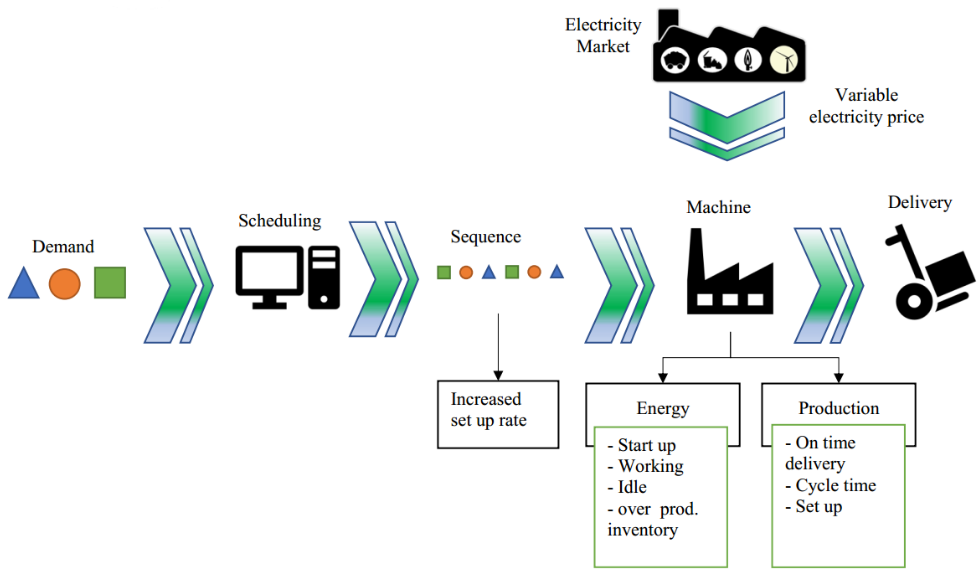


Figure 3.1: Lean energy production

3.2.2 Electricity market

The need for deregulation of power market has rooted in many technical, economical and environmental purposes [24]. Deregulation of electricity market brought up new philosophies in power generation, transmission, and distribution. These new concepts led to the *Smart Grid* [25]. The complex dynamic between demand, production and network topology as well as reliability concerns on one side and economic consideration, on the other hand, caused Demand Response (DR) programs to be an important and inevitable part of a Smart Grid. Two main types of DR has been discussed in the literature as a) incentive based b) price based [26]. The objective of price based (PB) programs is to transfer the market price variation to the customer side and make them adjust their consumption accordingly [27]. PB has different categories like real-time pricing, time of use, critical peak pricing, etc. In this study, the opportunity of real-time pricing (RTP) will be considered for reducing energy cost and consumption in a manufacturing process. In this chapter, it is assumed that the consumer is aware of hourly electricity price before the start of production by either a day ahead market or using available price prediction techniques.

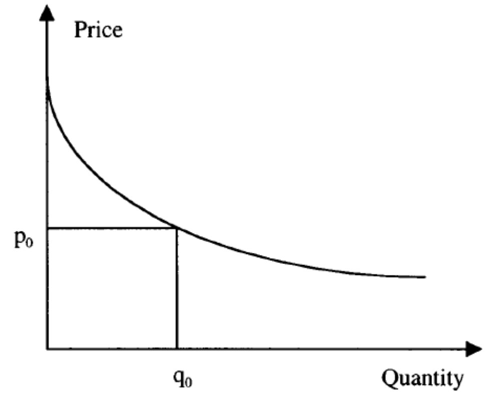


Figure 3.2: Demand price curve

3.2.3 Related literature

Responsiveness of demand is a measure used to quantify change of loads as the result of participating DR programs. This measure is widely utilized in stochastic analysis and elasticity estimation. In most of the literature for estimating demand response potential, sale-price elasticity function has been adopted from business studies as in Fig. 3.2 [28, 29].

The main weakness of these models is that they don't take into account the complexity of consumer's decision making process in electricity market which is significantly different from other commodities.

Some studies considered energy as a part of customer's decision-making process. Lau *et al.* considered one energy state (working) in a time of use (TOU) market in production planning. TOU market has only two pricing intervals, peak-time and off-peak-time [30]. Sun and Li used considered the following four energy states: full operation, partial operation, ready for production, turned off [31]. They used Markov Decision Process to estimate the reaction of customers to market events. Shrouf *et al.* used a single machine single product considering idle, working, start-up and shut down energy consumption state in heuristic scheduling model in a Real Time Pricing market [32].

As it discussed, some researchers focused on utility company without modeling the decision-making process of electricity customer while other researchers focused on the customer side and incorporating energy to production planning without connecting that to the concerns of the utility company. In this chapter, a full bottom-up analysis will be done using an energy based production planning and design of experiment.

In the current study, a mathematical model has been introduced to incorporate energy consumption in production scheduling in order to replicate the decision-making process with practical constraints. Other than energy consumption, the financial situation of the country or region, volatility of electricity price, demand for products and etc. can affect the response to the changes of price. These factors will form a DOE model which finally gives us a distribution for estimating responsiveness of demand in different situations of the electricity market.

3.3 Production planning: Model 1

In this section a mathematical model will be introduced for production planning in 8 hour shift which not only considers production constraints but also cost of energy during production. The model is capable of handling different electricity price for different scheduling intervals.

3.3.1 Mathematical model

Objective function

The objective function is trying to minimize total cost of production and direct electricity cost at the same time.

$$
\begin{gathered}
min \sum_{t=1}^{T} \sum_{i=1}^{I} (cp_i + ep_i \times C_t) \times p_{it} + (cq_i + eq_i \times C_t) \times q_{it} \\
+ \sum_{t=1}^{T} v_t \times (StC + StE \times C_t) + \\
\sum_{t=1}^{T} \sum_{t=1}^{I} ((psu_{it} - nsu_{it}) \times (sc_i + se_i \times C_t)) \\
+ \sum_{t=1}^{T} iE \times idle_t \times C_t
\end{gathered} \tag{3.1}
$$

Since back order is not acceptable in the model, material cost is considered to be constant. On the other hand, labor cost is assumed to be constant in one shift however they change among shifts which will be considered in model 2.

$$
\begin{gathered}
min \sum_{t=1}^{T} \sum_{i=1}^{I} ((ep_i \times C_t) \times p_{it} + (cq_i + eq_i \times C_t) \times q_{it}) \\
+ \sum_{t=1}^{T} v_t \times (StC + StE \times C_t) + \\
\sum_{t=1}^{T} \sum_{t=1}^{I} ((psu_{it} - nsu_{it}) \times (sc_i + se_i \times C_t)) \\
+ \sum_{t=1}^{T} iE \times idle_t \times C_t
\end{gathered} \tag{3.2}
$$

Demand constraint

A set of technical constraints has to be met in the scheduling process. The first constraint forces the production planning model to meet the demand for each product type at the right time.

$$q_{i,t-1} + p_{it} - q_{it} = d_{it}, \ \ \forall t = 1, ..., T \tag{3.3}$$

set-up constraints

An item cannot be produced unless the machine has the required set-ups. If any amount of type i is produced in period t, production set-up variable psu_{it} has to be 1, otherwise it should be 0.

$$if \, p_{it} > 0 \; then \; psu_{it} = 1 \, else \, psu_{it} = 0$$

psu_{it} is a binary and p_{it} is integer variable, so the following mathematical model satisfy the requirement:

$$\begin{cases} p_{it} - M \times psu_{it} \leq 0 \\ -p_{it} + M \times psu_{it} \leq -\varepsilon + M \end{cases} \quad \forall t = 1, ..., T \ \forall i \in I \tag{3.4}$$

ε is a small number, and because p_{it} is an integer variable, it can be anything between (0,1).

Initial and final set-up constraints

The constraints 3.5-3.10 assigns initial and final set-up to each time slot.

For each time interval, we will have an initial set-up from previous time step, and we might end with another set-up on the machine. If the initial set-up is the same as the final set-up of last period, we don't need to do the set-up. Thus, we have to assign a variable to remember the initial and the final set-up to each period.

If we have more than one set-up, the initial set-up and final set-up has to be different. However if we have only one item produced the initial and final set-up has to be the same. The following constraints will support this concept.

First we need to distinguish between planning intervals with one set-up and intervals with more than one set-up using a binary variable $para1_t$. If $\sum_{(i\in I)} psu_{it} > 1$ then $para1_t = 0$ otherwise $para1_t$ is equal to 1. The if-else condition can be written in a linear format as follows:

$$\begin{cases} \sum psu_{it} + M \times para1_t \leq 1.5 + M \\ -\sum psu_{it} - M \times para1_t \leq -1.5 \end{cases} \quad \forall t = 1, ..., T \tag{3.5}$$

The following constraints make sure that initial and final set-up are different if more than one type is produced:

$$\sum_{i=1}^{I} initial_{it} \times final_{it} = para1_t, \ \ \forall t = 1, ..., T$$

The constraint is not linear, but since the values of $initial_{it}$ and $final_{it}$ are binary, it can be converted to linear form. The conversion will not be free and we need to add two more constraints and one extra variable ($para2_{it}$). The linear form will be:

$$\begin{cases} initial_{it} + final_{it} - para2_{it} \leq 1 \\ -initial_{it} - final_{it} + 2 \times poara2_{it} \leq 0 \end{cases} , \ \ \forall t = 1, ..., T \tag{3.6}$$

$$\sum_{i=1}^{I} para2_{it} - para1_t = 0, \ \ \forall t = 1, ..., T \tag{3.7}$$

Initial and final set-up should be related to items produced in the interval. We need one extra variable for this purpose which is $para3_t$. If $\sum_{(i\in I)} psu_{it} \geq 1, \ \ para3_t = 0, otherwise \ \ para3_t =$

1

$$\begin{cases} \sum psu_{it} + M \times para3_t \leq .5 + M \\ -\sum psu_{it} - M \times para3_t \leq -.5 \end{cases}, \quad \forall t = 1, ..., T \tag{3.8}$$

$$initial_{it} - psu_{it} - para3_t \leq 0, \;\; \forall t = 1, ..., T \tag{3.9}$$

$$final_{it} - psu_{it} - para3_{it} \leq 0, \;\; \forall t = 1, ..., T \tag{3.10}$$

The production line can have only one set-up at the start and end of period.

$$\sum_{i=1}^{I} initial_{it} = 1, \;\; \forall t = 1, ..., T \tag{3.11}$$

$$\sum_{i=1}^{I} final_{it} = 1, \;\; \forall t = 1, ..., T \tag{3.12}$$

If $initial_{it} = final_{i,t-1}$ for each item i, new set-up is not needed and $nsu_{it} = 1$

$$final_{i,t-1} \times initial_{i,t} = nsu_{it}, \;\; \forall t = 1, ..., T$$

Like before, the nonlinear constraint can become linear at the cost of two additional linear constraints and a binary variable:

$$nsu_{it} = 0 \;\; for\, t = 1, \forall i$$

$$\begin{cases} final_{i,t-1} + initial_{it} - nsu_{it} \leq 1 \\ -final_{i,t-1} - initial_{it} + 2 \times nsu_{it} \leq 0 \end{cases}, \quad \forall t = 1, ..., T \tag{3.13}$$

Start-up constraint

If the line goes off during its idle times at interval $t-1$ and goes on during interval t, there will be a start-up.v_t is 1 if the line starts up at time t. The following constraint will take care of start-ups:

$$y_t - y_{t-1} - v_t \leq 0, \quad \forall t = 1, ..., T \tag{3.14}$$

Available time constraints

Constraint 3.15 considers the available time for production in each period. NoW_t represents the duration that line is not working at time slot t.

$$\sum_{i \in I} TU_i \times p_{it} + \sum psu_{it} \times st_t - \sum nsu_{it} * st_i \tag{3.15}$$

$$+StT \times v_t + NoW_t = PerTime, \quad \forall t = 1, ..., T$$

During NoW_t line can be off or idle, so the idle time has to be considered if the line remains on during no production time. Which can be written in linear form of:

$$NoW_t \leq idle_t + PerTime * (1 - y_t) \quad \forall t \tag{3.16}$$

3.3.2 Connection between production line and the utility company

The utility company needs to have an estimation about the reaction of customers to electricity market price volatility. As it discussed earlier, some researchers used business models to estimate the response of customers to change of price. These methods do not reflect the complexity of decision-making process in purchasing electricity. On the other side, some researchers modeled the decision-making process of customers in electricity market but did not connect it to the utility company. In this chapter, a DOE will be used to do a complete bottom-up analysis in an electricity market.

DOE also will be employed to study the impact of variables (factors) on the output (response) in an efficient and scientific way. DOE is referred to as the process of planning the experiment in which appropriate data will be collected and analyzed by statistical methods lead to a descriptive or predictive result. The entire process can be verified by statistical significance of the model at the end [33].

Every DOE model is recommended to have the following three preliminary steps [34]:

- Problem specification

We are interested in analyzing the effect of different working and electricity market condition on the production environment; consequently, the optimization model introduced in section sec. 3.3 has been considered as our study system.

- Response definition

The response is considered to be the amount of electricity demand that shifted from one hour to another. The absolute value of changes has been considered as response variable as follow:

$$Response = \frac{\sum_{\forall t \in H} |SD_t - RD_t|}{\sum_{\forall t \in H} RD_t} \tag{3.17}$$

- Factor selection

After the study system and response are identified, the affecting factors should be defined. Apparently, there are lots of factors that can change the response. In DOE, the researcher chooses a list of variables and assign two levels to each factor in order to capture the effects

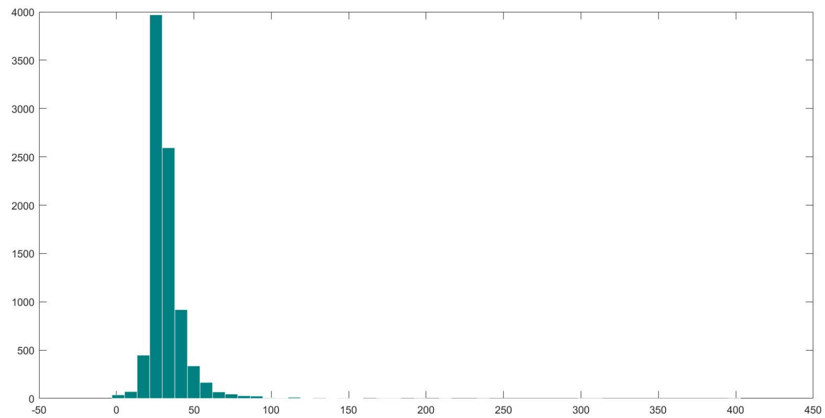


Figure 3.3: One year of hourly electricity price histogram

on response. The researcher has the option of running follow-up analysis with more factors or more levels on each factor if the result is not satisfactory [35].

Base on preliminary examinations, hourly demand, and electricity cost and its volatility is one of the main factors in the DOE. Start-up time and energy, set-up energy and time are the other significant variables. Idle energy can be considered in the DOE, but because of its minor effect in a preliminary analysis it has been excluded from the DOE but not from the mathematical model. Every variable or factor is considered to have two levels representing low and high. In the following subsections, each factor will be discussed, and low/high levels will be determined.

3.3.2.1 Analysis of factors and levels

Electricity price

The heart of PBDR is the variation of electricity price. In this section, one year of hourly electricity price has been analyzed. According to Fig. 3.3considering normal distribution might not be a valid assumption. Information criteria as a powerful statistical tool have been utilized in order to find the distribution of local marginal price (LMP) [36, 37]. Different information criteria metrics has been employed and reported. Each criterion will give a value associated with each distribution; the minimum number shows the best fitting model. Based on the results in Tab. 3.2 Gamma distribution shows the lowest value in every criterion and can explain the distribution of LMP in the best way.

Table 3.2: Information criteria results

	AIC	CAIC	SBC	ICOMP
Normal	71265.03	71281.18	71279.18	71261.14
LogNormal	71581.11	71597.27	71595.27	71577.22
Exponential	78307.05	78315.13	78314.13	78305.05
Gamma	67483.28	67499.44	67497.44	67480.23
Weibull	70358.041	70374.19	70372.19	70355.02

Table 3.3: Gamma distribution parameters

Parameter	Value	95% CI
Shape Par.	7.2301	(7.0237,7.4425)
Scale Par.	4.4425	(4.3113,4.5777)

Using Maximum Likelihood Estimators (MLE), the parameters for the Gamma distribution has been obtained and listed in Tab. 3.3. These parameters will be used in random price generation of DOE. The electricity price will not be one of the factors in the experiment but will be saved to analyze the effect of variance and range of price change on elasticity.

Product variety

A production line can produce different types of products. Three type of products has been considered as zero level, 2 types and 4 types construct -1 and +1 levels.

Production and demand

Demand for each type of products plays an important role in elasticity. According to the reports of "Industrial Production and Capacity Utilization" [38], manufacturing processes utilized a different percentage of their capacity during different years. The Tab. 3.4 shows how different capacities have been used in different years as a consequence of economy.

Based on the Federal Reserve data [38], the utilization of production line can be categorized into two levels based on economic condition: 63% and 85%. The demand for each production type will be produced based on a normal distribution with two levels of variance using the

Table 3.4: Capacity utilization in manufacturing

Time frame	% of capacity	Time frame	% of capacity
1972- 2014	78.6	2014-Oct	77.4
1988- 89	85.6	2014-Nov	78.1
1990- 91	77.3	2014-Dec	78.0
1994- 95	84.6	2015-Jan	77.4
2009	63.9	2015-Feb	77.1
2014 Mar.	76.8	2015-Mar	77.1

following parameters:

$$\mu_i = \left(\frac{Line\,Utilization}{Product\,Types}\right)/TU_i \tag{3.18}$$

$$x_3 = \sigma = \begin{cases} 0.1 \times \mu_i & Low\,Level \\ 0.15 \times \mu_i & High\,Level \end{cases} \tag{3.19}$$

Process time and energy consumption

In this paper, different states of energy consumption have been considered. Energy in the manufacturing environment can be categorized as a) direct energy b) supporting activities c) reducible states d) wasted energy d) environmental energy [39]. Direct energy and supporting activity's power consumption has been considered as production energy (ep_i). Reducible energy states have been taken into consideration as energy consumption during start-up. This energy section is inevitable but like the number of motor start-up or furnace, warm-up can be managed by a better scheduling approach. Wasted energy is the last part considered in the study which is idle energy [39]. Environmental energy (Lighting, HVAC, etc.) has been excluded from the scope of this chapter.

Although energy consumption levels and duration are related to the type of machines and devices in the line, using per-unit systems will simplify the approach. Material removal processes mostly require a short set-up and start-up time. Other demands like furnaces cause —higher electricity consumption and longer warm up (start-up) time. In addition to warm up, in some processes—especially food and chemical—the line has to run for a particular time in order to meet the standard property of the product. These situations have been considered in the model (section sec. 3.3). The start-up time (factor x_4) will have two levels 0, $\frac{1}{6}$ (10 minutes).

Since per-unit is utilized in this study, both furnace and motors will have 1 per-unit of consumption during full load. It is assumed that different types of product have various levels of energy consumption. The energy consumption for different kinds of goods will follow the subsequent distribution ($\mu = 1\, per - unit$):

$$x_5 = \sigma = \begin{cases} 0.1 & Low\, Level \\ 0.2 & High\, Level \end{cases} \tag{3.20}$$

Storage cost and energy for one hour can be expressed as a percent of production cost and electricity consumption. Storage energy will be considered in two levels 0% and 1% of nominal power. Holding cost as well is deemed to have 0% and 0.01% of production cost for one hour. Idle energy has been assumed to consume 10% or 20% of full load (1 per-unit). Set-Up time also considered taking 10% or 20% of an hour.

3.3.2.2 Full factorial design

There are 9 factors in the model each has two levels. Running all the possible combination of factor levels will sum up to $2^9 = 512$ different treatment combinations. There are many fractional factorial methods which can conduct the experiment with lower number of treatment combinations but since the experiment does not have any cost, full factorial design with 512 runs has been selected with D-efficiency and A-efficiency of 100% [35].

3.3.2.3 DOE results

The production planning model has been coded and optimized using *Gurobipy* for every treatment combination and the results fed into JMP for further statistical analysis. Screening analysis and half normal plot in Fig. 3.4 and variable selection summary in Tab. 3.6 shows despite all electricity price variations and parameters in the model the decisive factor that stands out significantly is the utilization of production line which is a function of economic condition. Having a very significant factor like x_2 in the case of large observations, will contaminate the variable selection and it is better to separate the results into two distinct analysis based on factor levels of x_2. Since each block of data includes 256 observation using

Table 3.5: Factor Levels

Factor	Description	Low Level	High Level
x_1	Type of products	2	4
x_2	Line utilization	63%	85%
x_3	Demand Variation	0.1	0.15
x_4	Start-up time	0	1/6
x_5	Energy variation	0.1	0.2
x_6	Storage energy	0%	1%
x_7	Storage cost	0%	0.01%
x_8	Idle energy	10%	20%
x_9	set-up time	10%	20%

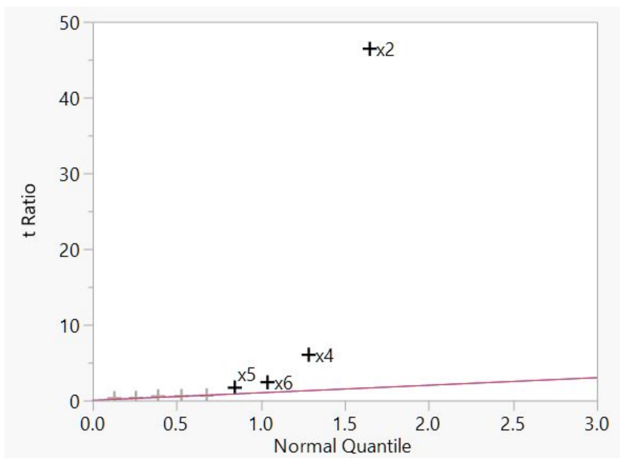


Figure 3.4: Half normal plot

$P-value$ might be misleading and $Corrected\,Bonferroni$ would be a better approach [35]. After separating the data and using the correction, factor x_4 will become significant for both blocks of data and will be added to x_2 as another important factor (Tab. 3.3.2.3). Considering these two factors and regression analysis, R^2 will be more than 84% which is satisfactory. In addition to R^2, Fig. 3.5 does not show any unexplained variation. Consequently, the selected factors and the full factorial treatment combination are statistically satisfactory.

Since utilization of production line has a decisive effect, a follow-up analysis has been performed. The studies related to line utilization [38] take into account inactive lines as well as active production lines, whereas DR managers are interested in active production lines and demands. Consequently, the follow-up analysis has been performed in the direction of increasing line utilization up to 90%. Fig. 3.6 shows unweighted distribution of demand

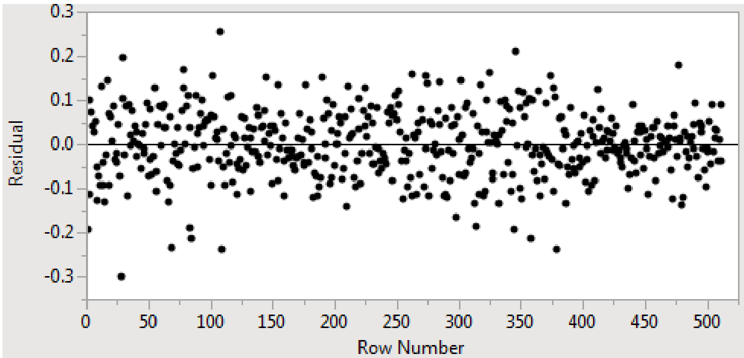


Figure 3.5: Residual by Row

Table 3.6: Variable Selection Summary

Treatment	*Pvalue*
x_2	$< .0001$
x_4	0.0004
$x_4 \times x_9$	0.0033
$x_1 \times x_3 \times x_6$	0.0045
$x_1 \times x_8$	0.0055
$x_2 \times x_5 \times x_7$	0.0163
x_6	0.0173

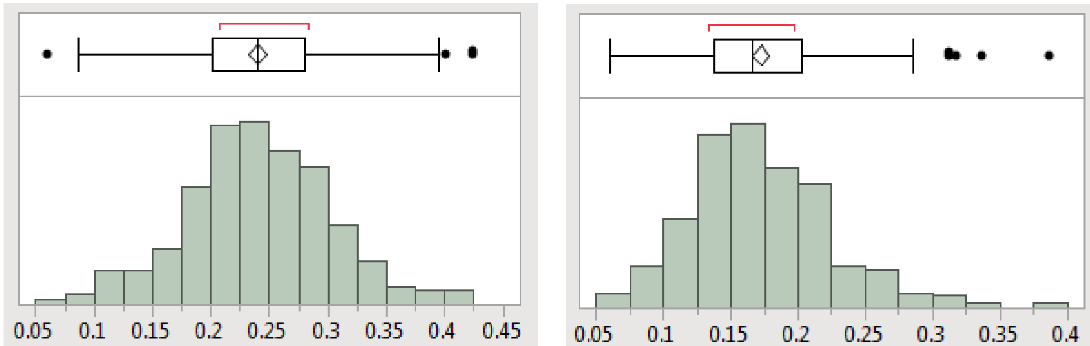
change for the most important factor (line utilization) which can be measured by economical indexes.

3.4 Production planning: Model 2

According to the previous section, economy is the most important factor. Economy determines the utilization of production lines, and consequently, in a recession, production lines have more flexibility to change their loads. Therefore, in a good economy with high uti-

Table 3.7: Adjusted Bonferroni

		Sig Prob	# Candidates	Adjusted Level
$x_2 = -1$	x_4	0.0001	9	0.0009*
	x_6	0.0819	8	0.6552
$x_2 = +1$	x_4	0.004	9	0.036*
	x_6	0.2054	8	1.6432



a) 85% line utilization

($\mu = 0.240, \sigma = 0.062$)

b) 90% line utilization

($\mu = 0.172, \sigma = 0.052$)

Figure 3.6: Distribution of load change

lization of line, the possibility of using demand response programs shrinks. In this section, another mathematical model will be introduced to optimize production planning considering the opportunity of moving some part of production to the second shift and save on energy. In this model, the cost of labor is considered to be higher during overtime hours.

3.4.1 Mathematical model

The mathematical model will be as follows.

$$\text{Min} \quad \sum_{t=1}^{T} en_t \times C_t + rt_t \times L \times LC_t \tag{3.21}$$

$$\text{s.t.} \quad p_t - q_t = d_t \qquad t = 0 \tag{3.22}$$

$$q_{t-1} + p_t - q_t = d_t \qquad \forall t \neq 0 \tag{3.23}$$

$$p_t \leq 0 + M \times (1 - z) \qquad t = 0 \tag{3.24}$$

$$-v_t \leq -0.5 + z \qquad t = 0 \tag{3.25}$$

$$y_t - y_{t-1} - v_t \leq 0 \qquad \forall t \neq 0 \tag{3.26}$$

$$TU \times p_t + StT \times v_t + NoW_t = PerTime \qquad \forall t \tag{3.27}$$

$$NoW_t - idle_t - PerTime * (1 - y_t) \leq 0 \qquad \forall t \tag{3.28}$$

$$TU \times p_t + StT \times v_t + idle_t - rt_t \leq 0 \qquad \forall t \tag{3.29}$$

$$en_t - ep \times p_t - eq \times q_t - v_t \times StE - iE \times idle_t = 0 \qquad \forall t \tag{3.30}$$

The objective function 3.21 tries to minimize the cost of energy and labor. Constraints 3.22 and 3.23 connect production and storage to demand. Constraints 3.24 and 3.25 force the line to start at first planning horizon (first hour) if there is any production.

Constraint 3.26 forces the start-up, if the line is being utilized at time t and was off during time $t-1$.

Constraint 3.27 is the time constraint, where production and start-up time has been considered as well as the time that line is not working (NoW). The line can run idle or be off when it is not working; constraint 3.28 will consider on/off during idle time.

Constraint 3.29 calculates the total running time. During the running time, labor has to be present at the line. So the model has to compromise between energy cost of running idle or going off. The last constraint (3.30) calculates the total energy consumption during each hour.

3.4.2 Model parameters

Depending on economy production lines will have different capacity utilization [40]. Different line utilization has been considered varying from 50% to 85%. It is assumed that each part occupies the machine for 3.5 minutes. Consequently, the number of parts will be:

$$\frac{Utilization * PerTime * hours}{TU} \tag{3.31}$$

For electricity price, one year of LMPs (local marginal prices) will be considered in this study. The data is available on California ISO website in 5 minute intervals. The closest temporal LMP has replaced the missing values.

Two shift has been considered; the first shift starts at 6:00 AM and finishes at 3:00 PM, when the second shift starts till 11:00 PM. The salary of a machinist is considered to be 1.5 times of regular salary for working over time.

The case study will be a CNC machine. In this example, an aluminum housing with dimensions of 150 mm x 50 mm x 25 mm is to be milled on a machining center with a work envelope of 850 mm x 700 mm x 500 mm. Heidenhein reported the energy consumption for manufacturing the part as table Tab. 3.8 [41].

Table 3.8: Mean power requirement for manufacturing a housing part

	Roughing	Finishing	Readiness
Cooling lubricant processing	5.1	1.5	0
Compressed air generation	1.3	1.3	1.3
Auxiliary components of the milling machine	3.1	2.8	2.5
CNC control package	.25	.25	.25
Spindle	3.25	1.55	0
Total	13 kW	7.4 kW	4.05 kW

Table 3.9: Number of extra shifts in a year

Salary Utilization	10 $	15 $	20 $
50%	17	1	0
55%	17	1	0
60%	31	4	2
65%	51	14	11
70%	51	14	11
75%	51	14	11
80%	86	43	31
85%	86	43	31

3.4.3 Result of extra shift analysis

Based on one year of LMP data and the model, the number of extra shifts is reported in table Tab. 3.9 based on different labor costs.

As it concluded in earlier this chapter, in a prosperous economy, companies cannot take advantage of different electricity price due to high utilization and lack of flexibility. In this section, a model has been recommended which creates flexibility by considering a possibility of running a second shift. In this case, companies with higher utilization can also benefit from changes in electricity price.

The results show that with the possibility of running second shift, highly utilized lines will tend to push more loads to second shift despite having to pay more labor cost.

3.5 Conclusion

In the current study three major steps has been taken in order to find the distribution of load change in RTDR. A novel hourly production scheduling and energy management tool has been introduced which can minimize the cost of manufacturing as well as electricity consumption concurrently. This chapter also emphasized the role of DOE in power market. DOE has been utilized to introduce a predictive model for the probability of demand change. The introduced distribution can be utilized in stochastic market modeling, demand response modeling, and other research topics. Another significant result showed that despite all the focuses on LMP variation in research and its effect on load shifting, variable selection emphasized that economy will be the most important factor for possibility and probability of direct load change. While the results suggest that low utilization of line provides more opportunity for participating in demand response, the second model has been recommended considering running extra shift which is more suitable for highly utilized lines.

4 An Improved Approach for Fuel Efficient Routing

4.1 Abstract

In a lean environment, smaller lot size results in more frequent deliveries and adds to the complexity of transportation. On the other side, transportation is one of the most discussed sources of waste in lean literature. In this chapter, two modes of carriers as private/dedicated and global/outsourced will be considered to reduce empty miles and variable cost. The most direct result of variable cost and empty distance reduction is less fuel consumption and

In this chapter, we will focus on concurrent optimal carrier selection and routing in a single objective optimization model. The decision-making tool is based on a new cost structure which is capable of reducing cost while keeping a high quality of service.

The complexity of vehicle routing problem and solution times convinced schedulers to settle with heuristic methods instead of exact algorithms and local optima instead of global optima. Different contract and strategies also limit the options for carrier selection and load assignment which results in billions of empty miles. In this chapter, a method for carrier selection will be introduced based on a novel cost structure.

4.2 Introduction

4.2.1 Overview

In this chapter, we focus on transportation as a part of supply chain. Transportation plays a major role in a supply chain. The connection between supplier, manufacturer, warehouse, and the customer is build using transportation. In a lean environment, transportation has been considered as a waste and should be eliminated. In addition to that, considering small lot sizes, the frequency of delivery increases and the problem becomes more complicated.

The effective and efficient utilization of transportation assets, including vehicle fleets, is a fundamental building block of a sound supply chain management practices [42, 43, 44]. However, in today's logistics environment, surface transportation challenges such as fuel costs, truck driver shortages, increased customer service requirements, industry capacity issues, rising insurance costs, heightened government regulations, and elevated environmental standards have increased the sense of urgency to improve efficiency by shippers and transportation providers as they seek to maintain performance [45, 46, 47]. Therefore, the problem of determining the optimal transportation network and vehicle fleet configuration to deliver products is complex [48], and implementation of that network also deals with difficult practical issues not always captured in strategic network design models [49]. Therefore, today's transportation practitioners continue to need improved tools for daily transportation decision-making that capture the intricacies of the capacity choices available for transportation, the dynamics of the demand, and the mix of performance objectives they hope to achieve.

Regarding capacity, shippers have a choice of three types of vehicle resources as they determine the assets that will service particular ground delivery lanes. These include private fleets, common for hire carriers, and dedicated trucking fleets that are "dedicated" to an organization and managed by a third-party provider. In recent research, an analytical modeling approach to determine the right size of a dedicated/private fleet has been offered by Rajapakshe et al., and in doing so highlighted the important strategic decision for determining the right sub-network size and capacity constraints for the dedicated/private fleet. However, they also describe "several practical challenges" for implementing a dedicated/private fleet approach in practice, including the inability to always meet the required volume [48]. Hence, they recommend creating an upper bound on the number of loads in each transportation lane when determining the size of a dedicated/private sub-network. This approach seems reasonable for making the a priori strategic decision for creating and sizing a dedicated/private fleet based upon anticipated demand and current capacity constraints, but in practice managers of existing dedicated/private fleets need to make daily decisions regarding how to utilize these resources when changes in demand and volume can exceed current capacity. Therefore, one transportation management approach that has increasingly become a solution for this problem is the use of common (third-party) carrier assets to supplement the existing network of dedicated/private vehicles [50]. This strategy can allow firms to create short-term capacity to match real world fluctuations in demand and realize the benefits often attributed to dedicated and/or private fleets while managing variation in demand with common carrier resources. In doing so, managers must make the important decision about which loads to assign to their dedicated/private vehicle network versus what loads to outsource on a daily basis to common carriers, but as will be discussed below the available academic models do not provide the ability to make this decision with a single objective model utilizing the decision-making criteria prioritized by practitioners when dedicated/private assets are allocated periodically [51].

This chapter first describes the problem within the context of the industry partner and sponsor for this research. The firm, hereafter referred to as Transportation, Inc., is a global Fortune 500 transportation firm that manages dedicated fleets for other major corporations, and thus faces the carrier assignment decision described above on a daily basis. Next, a short review of the literature is presented to assess current models for addressing dedicated/private versus common carrier assignment, gaps in the literature that need to be addressed to satisfy current industry needs, and the foundational literature used to develop the model presented in this paper. Next, the model and initial results using actual data from the industry partner are presented in order to assess the performance of the proposed model relative to current methods. The paper then concludes with both theoretical and managerial implications of the new model, a description of its utilization at Transportation, Inc., and a discussion of how to improve decision-making in this area in future research.

4.2.2 Physical description of model

Transportation, Inc. is a Fortune 500 dedicated vehicle fleet management and supply chain management services company in the United States that manages shipments around the world. As one of its primary business services, Transportation, Inc. allocates truck and trailer capacity to dedicated customers based on historical shipment data, which is a common strategy in private and dedicated fleet management [52, 53]. Its business model has traditionally been to re-allocate these resources approximately every three months (quarterly), with the goal of dedicating enough resources to each customer to ensure satisfactory service levels without over-assigning resources such that asset utilization suffers. They thus use common carriers in addition to dedicated/private fleet in order to supplement Transportation, Inc. resources that are assigned to a customer, as well as to take advantage of any situations in which common carriers are the best cost alternative.

The better cost of common carrier has two reasons. First, common carriers have more flexibility in accepting loads from different customers and can find better routes with less empty miles. Second, common carriers are geographically distributed and can be closer to pickup and delivery point and consequently less empty miles.

The Transportation, Inc. has three depots for its trucks dedicated to a costumer. In each depot, there are 20 trucks all the same size. There is a network of suppliers and customers for all three production facilities. The customers and suppliers are not completely separated, and there is overlap in regions.

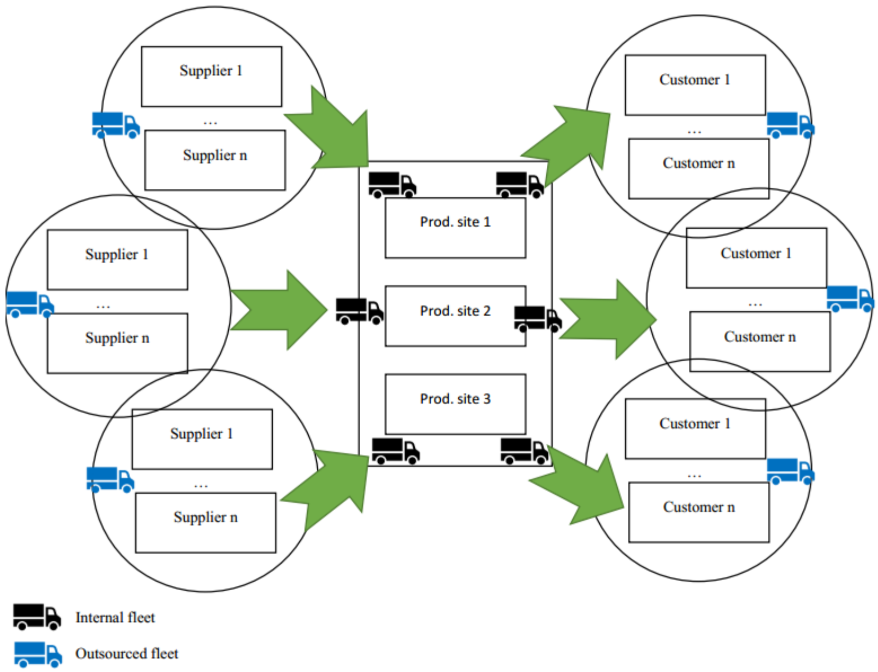


Figure 4.1: Physical attributes of model

4.2.3 Logical description of model

Travel time and distance are the heart of vehicle routing problem and have been considered in the model. Each load has the earliest pickup and latest delivery time. US Department of Transportation has regulations regarding maximum working hours of drivers which have been considered in the model. The data provided by Transportation, Inc. is a set of pickup and delivery loads for a week. All loads are assumed to be full-truck, and no consolidation is required.

The general overview of the model can be seen in Fig. 4.1.

4.2.4 Problem Background

Transportation, Inc. encounters the same problems with this business model as many other companies, which is that their internal shipment assignment systems, as well as available academic models, do not account for all of the factors they deem relevant in a single-objective model [51]. More specifically, the algorithms in their current transportation management software are primarily based on direct route cost, and the company bases the decision of which shipments to assign to their dedicated fleet versus common carriers on other factors such as timeliness (customer service), the ability to return Transportation, Inc. drivers to their home depot at the end of each shift, the backhaul probability of each route, and maximizing the utilization of internal assets. This dilemma drove Transportation, Inc. to determine which routes were given to their dedicated/private resources versus common carriers using a combination of both manual and automated methods in advance of the actual automated process of scheduling specific vehicle routes. This dilemma and its potential inefficiencies formed the basis for this research, as Transportation, Inc. recognized an opportunity to integrate these steps into a single decision model that more efficiently and effectively allocates and assigns different resource types to routes. The resulting model has since been commercialized by Transportation, Inc., and was successfully launched as a routing tool during the summer of 2015.

4.2.5 Related literature

4.2.5.1 Dedicated/private versus common carrier models

The decision of whether to assign a certain number of dedicated trucks to a customer or use common carrier capacity has been discussed in the literature in the past [54, 55, 56]. A key outcome from this body of work is that, while cost can be reduced, this is not purely a cost-related decision, and firms must evaluate strategic, tactical, and operational factors from both a direct and indirect perspective when determining the right solution for their organization. The key benefits of private and dedicated fleets are the increase in customer service from dedicated/private resources, higher service quality, increased control, and more flexibility [52]. Accordingly, a key step in developing more applicable models for practitioners is the realization that a more comprehensive total cost of ownership perspective that incorporates multiple decision factors should be used when developing a vehicle fleet assignment strategy [54, 57, 58].

Regardless of the transportation strategy chosen, if dedicated or private vehicle resources are part of that strategy, then it is unlikely that the organization will allocate enough dedicated/private resources to handle all shipments due to low asset utilization of unused capacity during off-peak periods [59]. Additionally, common carriers can offer lower cost for certain routes such that it may not be as economical to operate dedicated/private fleet assets on those particular routes. Thus, a key tactical decision that must be addressed is what shipments to designate to dedicated/private fleet resources versus those that should be assigned to common carriers.

As illustrated in Tab. 4.1, current fleet assignment models used by the transportation industry for implementation of this strategy rely on traditional cost models that are often based on both direct fixed and variable costs. These models tend to result in low utilization of dedicated/private resources relative to carrier preference [52, 60]. This forces a majority of providers to still employ manual methods to create routing assignments based on qualitative decision factors such as route preference and perceived quality, while those who do apply modeling approaches often use models that do not incorporate some of the most important objectives identified by transportation practitioners [51].

There is thus a gap between the current modeling parameters shown in Tab. 4.1 and the actual factors that influence the dedicated/private resource versus common carrier assignment and routing decision in practice. Many dedicated/private carriers allocate resources periodically, and thus fixed costs are essentially sunk until the next periodic reallocation cycle. Models that incorporate this feature along with other relevant factors specified by Transportation, Inc., such as time sensitivity, returning drivers to their home depot, and utilization of Transportation, Inc. resources, in a single-objective model would advance the academic literature and provide practitioners with more effective analytic models.

4.2.5.2 Vehicle Routing

While the cost structure used to formulate the objective function and associated constraints of the models presented in the current literature needs to be improved to reflect current decision-making criteria, the foundation of a new model can still be based on existing scheduling and routing models and techniques for assigning resources. Hence, the problem in this research described above can be categorized as a vehicle routing problem (VRP) in which a number of customers need to be served by a fleet of vehicles [61]. The body of literature focused on the VRP was first introduced by Dantzig more than fifty years ago as a special case of the travelling salesman problem [62]. Subsequently, many approaches have been utilized to formulate VRP, and the literature has expanded to three main variants of the original model concerning time windows, backhauls, and pickup and delivery [61]. Additionally, there are multiple methods that have been used to model these formulations, such as Eilon, Watson-Gandy, and Christofides [63] who modeled VRP as a dynamic programming problem or Baldacci, Hadjiconstantinou, and Mingozzi [64] and Balinski and Quandt [65]

Table 4.1: Research addressing carrier selection and routing problem (VRPPC)

Paper	Overview	Carrier selection and VRP
Chu (2005)	• Assumes full utilization of owned truck • Assumes the freight charged by the LTL carrier is usually higher than the cost handled by a private truck. • Carrier selection and routing in two steps • No time window constraint	• Order the customers in ascending order based on the freight charged by the LTL carrier. • Assign loads to owned truck based on the order • Assign the rest to the third party • Heuristic for private truck routing after load assignment
Bolduc, Renaud, and Boctor (2007)	• Assumes full utilization of owned truck • Carrier selection and routing in two steps • Does not compare private cost with CC cost • No time window constraint	• Order the customers based on third party cost • Assign the loads to external carrier from top until full capacity of owned fleet is utilized • Assign rest to the private fleet • Heuristic VRP for dedicated/private fleet after load assignment
Côté and Potvin (2009) Potvin and Naud (2011)	• Assumes full utilization of owned trucks • Carrier selection and routing in two steps • Does not compare private costs with CC cost • Penalty for assignment to common carrier • Considers fixed cost in model • If a customer is assigned to external carrier at the early step there is no chance to assign it to private carrier later in routing • No time window constraint	• Rank customers based on a normalization function • Includes common carrier penalty cost • Assigns customers until reaching private fleet capacity • Assign the rest to common carriers • Tabu search for routing (modified Tabu search using ejection chains)
Bolduc, Renaud, Boctor and Laporte (2008)	• Carrier selection and routing in one step • Changed variables and made the problem smaller • Added fixed cost to the travel cost from depot • No time window constraint	• Cost comparison at the same time with routing problem to select the carrier
Liu, Jiang, Liu, and Chen (2010)	• No upper bound on number of private • Carrier selection and routing in one step • Can accept loads from other companies • Fixed cost in objective function and carrier comparison • No time window constraint	• Cost comparison at the same time with routing problem to select the carrier • Mathematical model developed to solve fast with accept lower bound
Kratica et al. (2012)	• Modified Genetic algorithm based on cost • More focus on computation time • Fixed cost in objective function and carrier comparison • No time window constraint	• Cost comparison at the same time with routing problem to select the carrier

who have both modeled VRP as a set partitioning problem. The variants of the VRP over the last fifty years are described and categorized in recent reviews by Eksioglu et al [66], Lahyani et al. [67], and Braekers et al. [68].

Established formulations from the literature can be utilized as a baseline for solving the dedicated/private resource versus common carrier routing problem described in this paper. The VRP with pick-up and delivery ($VRPPD$) is a generalization of the classic m that has been formulated by Desaulniers, Desrosiers, and Solomon [69] for use when there is a need to transport demand between a pickup and delivery point. While this formulation is useful, many times these pickups and deliveries involve a time window that must also be considered. In this case, each load has to be carried in a specific timeframe, and thus the $VRPPD$ with time windows ($VRPPDTW$) class of problems has been formulated to address both constraints in the same formulation [69, 70]. The related vehicle routing problem with private fleet and common carrier ($VRPPC$) was discussed in Tab. 4.1, and is a specialized form of the problem that allows fleet assignment to different types of assets. Hence, a generalization of $VRPPDTW$ and $VRPPC$ is introduced in this paper, and assigns and routes dedicated/private assets versus common carrier resources for specific routes in a distribution network within a single model.

4.3 Model formulation

Tab. 4.2 presents the mathematical structure and definitions used to develop the optimization model. In this section, a new cost structure is recommended and utilized in the objective function of the model, and additional practical constraints are also introduced into the formulation. As such, this improved optimization model provides an important extension to the previous baseline modeling work on the $VRPPDTW$ by Desaulniers et al. and Dumas et al. that allows dedicated/private transportation providers to more accurately assign and route transportation assets according to the decision factors that they value in practice [69, 70].

To construct the model, three major mathematical sets need to be defined: Nodes, Loads and Routes. Two nodes (departing and returning) are assigned to a depot. The first of these nodes (node 0) is assigned to the depot and is utilized as the departing node, and the second node is assigned to the same depot as the returning node (node 1). Thus, node 0 and node 1 are actually the same point, but separated for mathematical modeling convenience. Each load is considered to be a full truck load and after pickup, the only option is the corresponding delivery node. Consequently, the pickup and delivery points can be considered as one node [69].

Additionally, two other decision rules related to time were added based on conversations with Transportation, Inc. These two rules are below, and could easily be removed as a constraint if they do not correspond to another firm's decision-making process.

- A lower bound of thirty minutes is required for the service and wait time (tsw_{ij}). This requirement was added based on feedback from Transportation, Inc. that there is some minimum time period for a vehicle to arrive at and leave a location regardless of any other waiting requirements.
- An upper bound of fourteen hours is necessary for the total working time due to US Federal Motor Carrier Safety Administration regulations on driver service time.

4.3.1 Mixed fleet cost model

As discussed above in Tab. 4.1, most traditional cost models for the $VRPPDTW$ were established based on a single carrier model (private, dedicated, or common carrier), and not a combination of them. Those models that did allow selection of different types of carriers primarily utilized direct costs (all models in Tab. 4.1). The reliance on only these direct costs forces shippers to develop multi-objective or multi-criteria decision-making methods outside of the model that allows them to integrate other decision factors into the process. In this section of the paper, a novel cost structure is introduced that allows the problem to be solved using a single objective model for carrier selection of routes. The objective of the model is minimization of cost, and thus both dedicated/private asset and common carrier costs are considered in the objective function:

$$Min \sum_{k \in \{v_1, v_2\}} (c_{ijk} * x_{ijk})$$

Researchers have typically derived the elements of travel cost in the VRP with a high level of precision and then combined cost components into a single cost model. Similarly, Tab. 4.3 is an overview of the dedicated/private asset cost breakdown that is used to determine costs within this model. These components are based on working with Transportation, Inc. to

Table 4.2: Nomenclature

Sets and Indices	
i, j, h	Node indexes
k	Vehicle number index
$v = \{v_1, v_2\}$	Set of all vehicles; $v_1$is the set of dedicated/private fleet and v_2 is a set with one member representing all common/global carriers.
N	Set of nodes
Parameters	
c_{ijk}	Cost of traveling from deliver node of load i to pickup node of load j with truck k
NT	Number of utilized trucks
FC	Fixed cost
TC_{ijk}	Travel cost from i to j for vehicle k
s_i	The time that node has been visited by a vehicle $\forall i \notin N\{1, 2\}$
t_{ij}	Travel time from deliver node of load i to pickup node of load j with truck k
tsw_{ij}	Service and wait time for dedicated vehicle at route (i, j) with lower bound of 30 minutes.
w_{1k}, w_{2k}	The time that node 1 or 2 has been visited by vehicle k
WT	Upper bound for working time, $WT = 14$ hours Working time is equal to all driving time, service time and waiting time between loads.
Decision Variables	
x_{ijk}	$\begin{cases} 0 & \text{vehicle } k \text{ uses rout } (i, j) \\ 1 & otherwise \end{cases}$

Table 4.3: Transportation cost components at Transportation, Inc.

Fixed cost	Travel cost – route cost	Travel cost - per mile
Equipment purchase (Truck, trailer, etc.)	Cost of road characteristics	Fuel consumption
Depreciation (salvage)	Number of stops	Driver (wage, benefits, etc.)
Maintenance and inspection	Toll	Maintenance
Special permits		
License fees, insurance fees, etc.		
Management and overhead (Office space, office equipment, management salary and expenses, advertisement, communication, etc.)		

understand how they decompose their cost structure in practice when making the mixed fleet assignment and routing decision.

Transportation, Inc. currently divides the overall cost of dedicated/private assets in Tab. 4.3 into three categories: fixed cost, travel fixed cost, and travel variable cost. The first cost segment is fixed cost, and this part consists of all overhead (management, office, etc.) and capital investment (truck purchase, required business licenses, permits, insurance, etc.) costs. Some part of maintenance activities are fixed, as an oil change for example has to be done based on mileage or time, whichever comes first. Time-based maintenance costs are considered in this part. Travel cost can be divided in route dependent and mileage dependent components. The route dependent travel cost includes costs such as road quality, traffic, tolls, and average number of stops. The mileage dependent portion consists of costs such as fuel consumption, some proportion of driver salary and distance related maintenance like tire and belt changes.

Fixed cost is inherently different from the other two categories. This cost segment is constant regardless of how many dedicated trucks are being utilized because Transportation, Inc. allocates their resources to customers on a periodic basis. Thereby, this part of the cost is not avoidable and should be excluded from comparison between dedicated/private assets and common carriers on a tactical level. However, it should be noted that fixed cost should be considered in fleet sizing decisions as a component of analysis when deciding how many internal resources to allocate across parts of the network, but we are assuming this decision has been made in advance of the daily assignment decision (as is the business model of Transportation, Inc. and other large dedicated/private carriers). The following calculations will illustrate this concept mathematically.

Traditionally, fixed cost, like any other cost element, is divided by the total number of trucks or traveled miles. In this case, the cost associated with private or dedicated trucks will be:

$$c_{ijk} = \left(\frac{FC}{|v_1|} + TC_{ijk}\right) \quad k \in v_1$$

where $|v_1|$ is total number of private/dedicated trucks.

Daily truck utilization can be described in many ways, but the simplest definition is:

$$u = \frac{Number\,of\,utilized\,trucks}{|v_1|}$$

In this situation the fleet management company, Transportation, Inc., will charge its customers all travel costs and a portion of fixed cost as follows:

$$Customer's\,overall\,cost = FC * u + \sum_{\forall i,j,k} (TC_{ijk} * x_{ijk})$$

A hidden cost is created when allocating the fixed costs in this manner, as the objective function only considers the actual number of trucks utilized as part of fixed costs even though all trucks are fixed to a customer given the periodic allocation process. Consequently, the following part of fixed cost is not considered in the objective function:

$$Hidden\,cost = FC * (1 - u)$$

Therefore, the fixed cost has to be divided by the number of utilized trucks instead of total trucks in order to capture all the relevant costs for the daily decision. The cost of each utilized truck k will be:

$$Assigned\,asset\,cost = \frac{FC}{|v_1| * u} * |v_1| * u + \sum_{\forall i,j,k} (TC_{ijk} * x_{ijk})$$

The denominator in first element will be canceled with $|v_1| * u$ and the remaining term will be fixed cost, which is constant. The following linear equation will thus be the resulting objective function:

$$minimize \sum_{\forall i,j,k} (TC_{ijk} * x_{ijk}) \tag{4.1}$$

The same result can be obtained by considering actual traveled miles instead of utilized dedicated/private assets in the problem formulation. Consequently, fixed cost should not be considered in the tactical decision making between dedicated/private assets and common carriers when using a periodic allocation strategy such as the one at Transportation, Inc. and other dedicated/private transportation providers that view the assignment of resources to facilities in the network as a strategic decision that is made periodically based on projected demand and desired service levels within the network.

Among elements of travel cost, fuel cost needs a higher level of attention.

4.3.2 Fuel cost

As it concluded so far, in the comparison between internal and global carriers, the variable cost of internal fleet should be compared with outsourced fleet cost. Fuel cost is the main part of variable cost and while some studies consider fuel consumption to be a constant per-mile rate, different researchers stated that fuel consumption is not constant and can be affected by speed, road gradient, wait times, and payload [12, 71].

According to Suzuki, the impact of speed and road gradient can be considered as follows:

$$c_{ij} = (\alpha_0 + \alpha_1 v_{ij})\gamma_{ij} \tag{4.2}$$

in the above formula, γ is the road gradient factor, and v represents speed. $\alpha_0, \alpha_1$are parameters that has been estimated by researchers [12].

The impact of payload on fuel consumption can be factored as:

$$\pi_{ij} = \frac{\beta_0 + \beta_1 \sum_{i \in \gamma_{ij}} l_i}{\beta_0 + \beta_1 \mu} \tag{4.3}$$

During wait times trucks consume fuel since the driver mostly leave the engine running. The constant hourly rate of ρ. Then according to Suzuki, the real fuel consumption will be:

$$\sum \sum \frac{d_{ij}}{c_{ij}\pi_{ij}} x_{ij} + \sum (B_i - A_i) \frac{\rho}{60}$$

The tests show that since all loads are considered full truck and the data belongs to flat area of Louisiana and Texas, the exact fuel model does not change the decisions.

4.3.3 Mathematical model

The impetus for this model was to accurately reflect the decision factors used in practice in the dedicated/private fleet versus common carrier assignment decision, and thus the development of the model constraints in the continuation of this section are based on working with Transportation, Inc. to understand their current processes for assigning and routing their dedicated fleets. There are some business strategies that are relevant for dedicated/private resources that are integrated into the model, but are not included for common carrier resources. The key differences regarding how constraints are applied to private/dedicated versus common carrier resources are as follows:

- Routing of common carriers is not a point of interest. We just consider single load handling without consideration for common carrier truck routing before picking up and after delivering a load.
- It is assumed that the common carriers will take care of time window and maximum working hour regulations externally from the model.
- Leaving from and returning to a depot is not a concern for common carrier resources.

The mathematical model will be as follows:

$$
\begin{aligned}
\text{Min} \quad & \sum (TC_{ijk} + TC_{jj}) * x_{ijk} && && (4.4)\\
\text{s.t.} \quad & \sum_{\forall j \notin \{0,i\}} \sum_{\forall k} x_{ijk} = 1 && \forall i \notin \{0,1\} && (4.5)\\
& \sum_{\forall h \notin \{1,i\}} x_{hik} - \sum_{\forall j \notin \{0,i\}} x_{ijk} = 0 && \forall i \notin \{0,1\} && (4.6)\\
& \sum_{\forall i \notin \{0,1\}} x_{i0k} = 0 && \forall k \in \{v_1\} && (4.7)\\
& \sum_{\forall j \notin \{0,1\}} x_{1jk} = 0 && \forall k \in \{v_1\} && (4.8)\\
& \sum_{\forall j \notin \{0\}} x_{0jk} = 1 && \forall k \in \{v_1\} && (4.9)\\
& \sum_{\forall i \notin \{1\}} x_{i1k} = 1 && \forall k \in \{v_1\} && (4.10)\\
& s_i \leq TDel_i && \forall i \neq 0,1 && (4.11)\\
& s_i - t_{ii} \geq TPic_i && \forall i \neq 0,1 && (4.12)\\
& w_{1k} - w_{0k} \leq MaxDri && \forall k \in \{v_1\} && (4.13)\\
& w_{0k} - w_{1k} + M * x_{01k} \leq M && \forall k \in \{v_1\} && (4.14)\\
& w_{0k} + t_{0j} + t_{jj} + ts_{0j} - s_j + M * x_{0jk} \leq M && \forall i \neq 0,1, \forall k \in \{v_1\} && (4.15)\\
& s_i + t_{i1} + t_{11} + ts_{i1} - w_{1k} + M * x_{i1k} \leq M && \forall i \neq 0,1, \forall k \in \{v_1\} && (4.16)\\
& s_i + t_{ij} + t_{jj} + ts_{ij} - s_j + M * x_{ijk} \leq M && \forall i \neq 0,1, \forall k \in \{v_1\} && (4.17)
\end{aligned}
$$

The objective function in equation 4.5 shows the cost of traveling from node i to node j and pick up the load at node j and deliver it. is travel cost per mile for dedicated trucks and will be 0 for common carriers. Constraint 4.6 makes sure that all the loads has been taken care of. Constraints 4.7-4.11 force each dedicated truck to start from depot travel from each node to another and finally go back to depot, this constraint does not prevent subtour elimination. Constraints 4.12-4.13 considers time window for delivery and pick up and 4.14 limits the travel time to the required hours. Constraints 4.15-4.17 take care of travel time and at the same time they eliminate subtours.

The most complex part of a VRP is subtour elimination constraints. Generally a subtour elimination constraint can be considered as follows:

$$\sum_{i\in S}\sum_{j\in S} x_{ij} \leq |S| - 1 \quad \forall S \subset V, \ \ |S| \geq 2$$

the number of connectivity constraints grows as the number of subset of a given set with the size of $O(2^{|V|})$.

Miller, Tucker and Zemlin [61] recommended a set of SEC for VRP with a capacity which has polynomial cardinality as follows:

$$u_i + d_j - u_j + M * x_{ij} \leq M$$

The great idea of Miller reduced the size of CVRP significantly. In this paper, a subtour elimination constraint will be considered based on Miller's idea that can be applied to all classes of TSP and VRP even without capacity constraint.

If we assign a number to the first node in the route and every time we reach another node we assign a number to the destination node greater than the origin number subtours can be eliminated.

Proof: Using contradiction, if a route starts from node i and assign s_i to this node, every other node has an assigned number s_j greater than s_i. If the traveler wants to traverse the arc between a node k in the route to node i, then $s_i > s_k$but we already mentioned that all the nodes in the route including k has $s_k > s_i$ which is a contradiction.

So considering a constraint like:

$$s_i + \alpha + s_j + M * x_{ij} \leq M$$

Where α is any positive number, will satisfy subtour elimination with polynomial cardinality for every class of TSP including VRP. As an example consider a route from node 1 to 2 to 3 in figure Fig. 4.2. If we assign 1 to node 1, with $\alpha = 1$ then we have to assign 2 to node 2 and 3 to node 3, since we are going to node 1 from 3 and node 1 has been labeled 1 already and with this rule it has to become 4, contradiction happens and the solution will be infeasible.

In case of VRP, we can consider α to be the travel time between nodes. In this case both travel time and subtour elimination satisfied at the same step.

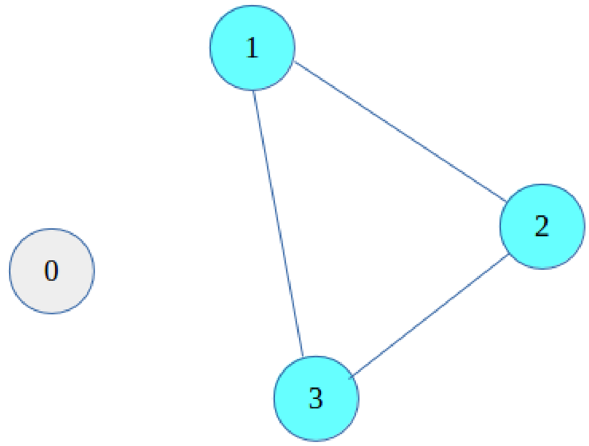


Figure 4.2: Subtour Example

The size of this new problem will be $O(|V|^3)$ which is a much better and smaller model.

4.3.4 Umbrella constraint detection

VRP has been developed in a way to consider all possible situations and routes, specially using traditional exponentially growing SEC. Some of the constraints will be binding and restricting feasible region but some will not have any impact on the model. Those non-binding constraints will not have any impact on result but increase the size of problem and cost of calculation in each iteration. The calculation cost will be even higher in the case of mixed integer programming. *Branch and bound* solves the relaxed problem many times to find the integer solutions and *branch and cuts* adds the cost of finding cuts based on constraints. Calculation cost for both methods generally will increase significantly in the case of MIP due to the process. In figure Fig. 4.3 examples of binding and non-binding constraints has been demonstrated.

In this section we apply Umbrella Constraint Detection (UCD) methods to find non-binding constraints.

Definition 1 (Umbrella Constraint): Let ζ be the set of indices corresponding to all the constraints (rows) of an optimization problem, and let $j \in \zeta$. Constraint (row) j is an umbrella constraint of ζ if and only if removing it from ζ alters set of feasible solutions of the original optimization problem [72].

Definition 2 (Umbrella Set): The umbrella set of an optimization problem is the set

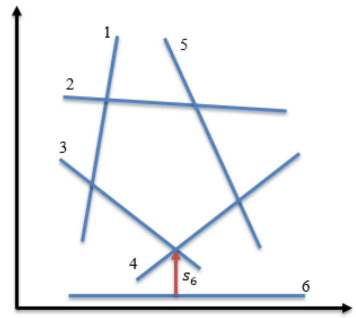


Figure 4.3: Binding and non-binding constraints

containing the minimum number of constraints (rows) necessary to form its set of feasible solutions. Removing any member of the umbrella set would alter the set of feasible solutions of the original optimization problem, while adding any of the constraints in the non-umbrella set, would not change the set of feasible solutions [72].

Ardakani and Bouffard proved that the following formulation would find the Umbrella Set for every linear problem.

For $s \geq 0$ for all $j \in \zeta$

$$s_j = \begin{cases} 0 & \text{if constraint j is umbrella} \\ > 0 & \text{otherwise} \end{cases}$$

s_j will be obtained from the following optimization model which can be ran on every

$$\begin{aligned} Min \quad & s_j \\ s.t. \quad & \\ & a_{j'}^T w_{j'} \leq b_{j'} \qquad \forall j' \in \zeta \\ & a_j^T w_j + s_j \geq b_j \end{aligned} \tag{4.18}$$

The formulation 4.18 adds s_j variables to the problem and makes the problem bigger, but there are opportunities to accelerate:

- Relax integrality: The problem can be optimized using integrality constraint, but it will not change the results and just makes the runtime longer.

- Decomposition: Model 4.18 can be solved separately for each s_j and might improve the time.

- Partial run: Some constraints play key role in the model and cannot be excluded. The UCD can test only nonimportant constraints. For example, travel time constraint can not be dropped because of its significant effect.

The following approaches have been considered:

1. Original problem without UCD
2. Complete constraint set
3. Partial constraints:
   a) Decomposed and sequential
   b) Decomposed and parallel
   c) Integrated problem

A problem with 20 loads has been considered from a transportation company as our case study. The models have been optimized using Branch and Cut and Gurobi.

The results in Tab. 4.3.4 show the impact of each approach on UCD:

Table 4.4: Different UCD method comparisons

	case 1	case 2	case 3.a	case 3.b	case 3.c
UCD Time	0	132.9920	3.3954	2.7127	0.1159
Optimization Time	3.3507	1.4166	1.4166	1.4166	1.4166
Total Time	3.3507	134.4086	4.812	4.1293	1.5325
% dropped const.	0	0.9979	0.9979	0.9979	0.9979
% time improvement	-	-3911.11	-43.6117	-23.2369	54.2632

4.3.5 Vehicle assignment and demand allocation

Based on the problem definition, dedicated vehicle and drivers need to be allocated to a specific home depot which is at a predetermined location in the distribution network. Thus, the solution approach needs to provide the ability to solve the problem for each depot and its allocated vehicles separately without having to solve for the entire network of loads simultaneously. A common method in the literature is to assign and allocate delivery locations to a given depot uses either 3-digit or 5-digit US Postal Zip Codes based on the distance between the centroid of the depot's zip code and the centroid of the potential demand location zip codes. This heuristic method for assigning locations to a depot or sub-region in a location problem is an accepted method and has been described by Simchi-Levi, Kaminsky, and Simchi-Levi, LeBlanc et al., Simchi-Levi et al., and others [73, 74, 75].

A 5-digit process was used in the solutions presented below, and this approach has two advantages in terms of the simplicity of the solution approach:

- In addition to decomposition, zip code clustering can make the model even smaller by forming a data dictionary on the first run that can also be used in future runs.
- Transportation, Inc. desires that its dedicated drivers return home each night for retention purposes. Although the optimization model can account for this strategy using time and coverage approaches similar to those used by Schilling et al., Ball, et al., Branas et al. and others, zip code clustering can also be used for this consideration by keeping private/dedicated drivers within a pre-determined geographic zone [76, 59, 77].

4.3.6 Solution approach

The model outlined in this paper allows carrier selection to be addressed concurrently with the pickup and delivery problem based on a cost minimization single objective problem with customer service and vehicle coverage constraints. The model was consequently coded in *gurobipy* and optimized using Gurobi solver. Actual Transportation, Inc. data is used to compare the results from this model to the results of other relevant solution approaches to the problem in order to illustrate the performance of the newly developed single objective model. In addition, sensitivity analysis is incorporated and leads to observations regarding further improvements as constraints are relaxed. These results are used to illustrate theoretical insights and managerial implications that can be built upon to improve this important decision-making process.

4.4 Results

4.4.1 Testing process

In this analysis, eight days of pickup and delivery load data from Transportation, Inc. was optimized in the model. Results were analyzed to determine the effectiveness of the model for decision making between private/dedicated assets and common carrier assets. Further analysis was conducted at Transportation, Inc. prior to commercialization of the model into their software suite to test performance. In addition to the newly developed cost model, two other models and solution approaches are considered to provide a baseline for comparison. The three models are described below.

- Model 1: the single objective model developed in this paper.
- Model 2: a second single objective model in which fixed cost associated to each truck is only added to utilized trucks. The objective function in this model is the same as Bolduc et al. (2007, 2008), which is one of the most cited cost models in carrier selection. These models do not address time sensitivity and business strategies, and thus constraints 2-9 have been considered with different objective functions to create a fair comparison of results.
- Model 3: as will be illustrated below, traditional cost models such as those used in Model 2 can result in poor private/dedicated fleet utilization. Thus, some software allows weights input by the user for dedicated/private and common carrier assets during carrier selection. Assigning higher preference weights to private/dedicated assets will result in larger utilization for these assets, which is the process Transportation, Inc. was using to eliminate as much of the manual intervention in the decision as possible. A weighted sum multi-objective model was used in this analysis by assigning a priority of two to Transportation, Inc.-owned assets, which was considered a moderate weight that gives a result close to Transportation, Inc.'s current decision-making process [78]. The weights and decision rules for this model were subsequently externally validated by experts at Transportation, Inc. as being representative of the actual process in which Transportation, Inc. sets the highest weight possible for the dedicated fleet in their software to force the use of that asset type.

An overview of the results shown in Tab. 4.5 and Tab. 4.6 demonstrate that using Model 1 results in a much more balanced decision process for minimizing costs, utilizing the assigned dedicated fleet, and considering vehicle coverage constraints. While the objective of the model is still cost minimization, Model 1 achieves the lowest travel cost compared to the other two models and 62.3% of loads are allocated to the assigned dedicated vehicles. Model 2, which was based on current, approaches in the industry over-utilized common carriers, a solution that would be unacceptable to Transportation, Inc. based on low utilization of dedicated trucks. This is why many carriers, such as the research partner, currently use manual or multi-objective approaches similar to Model 3 for assigning routes in which they use weights and then manually review the route assignments to reallocate some of the

Table 4.5: Summary results

	Model 1	Model 2	Model 3
Total loads	105	105	105
Number of loads carried by common carrier	39	102	10
Number of loads carried by dedicated	66	3	95
% carried by dedicated	62.9%	3.0%	90.48%
Variable cost	$ 81,993	$ 96,389	$ 83,957
Fuel saving	-	14.9%	2.3%

routes back to common carriers based on expert judgment. However, a similar approach, as illustrated by Model 3, resulted in more loads carried by Transportation, Inc. resources, but at a higher cost.

Model 1 combines the necessary decision making criteria into a single model. The loads assigned to common carriers by Model 1 were validated as satisfactory by Transportation, Inc., and similar to those that would have been assigned after a more exhaustive manual, posthoc process. However, it is shown that automating the process into a single optimization model is achieving efficiencies and cost reductions that the manual process at Transportation, Inc. may not be able to consistently achieve based on expert judgment alone. This is because this process is still dependent on exogenous inputs by the company's transportation managers in a trial and error process that does not guarantee an optimal solution.

Tab. 4.7 shows that the company can save a direct cost of $70,000 at only one depot per year by using Model 1 instead of their current approach. This is one of the main contributions of this model, as it can assign a high number of loads to dedicated/private trucks (similar to what is done in practice) due the cost structure being more representative of what is driving the actual decision in practice. There are also some other indirect costs (engineering, time, etc.) that can be saved by utilizing the recommended model, as the results of current multi-objective models need post-optimization analysis to provide the final solution. As stated, Transportation, Inc. subsequently validated the results in Model 1 as being a more consistently efficient solution than the previous manual post-hoc process could provide.

The model has been tested with a more accurate fuel consumption model [12] but the decisions related to carrier selection did not change while the cost changed.

Table 4.6: Number of dedicated/private vehicle utilized by day

Day	Model 1	Model 2	Model 3
1	8	0	9
2	7	0	10
3	9	0	12
4	4	0	17
5	3	1	8
6	7	0	12
7	1	0	1
8	4	0	4
Fleet size needed	9	1	17

Table 4.7: Travel cost

Day	1	2	3	4	5	6	7	8
Model 1	\$ 11,877	\$ 10,422	\$ 12,514	\$ 19,089	\$ 11,938	\$ 13,421	\$ 1,639	\$ 1,093
Model 2	\$ 13,233	\$ 12,748	\$ 15,787	\$ 20,098	\$ 12,014	\$ 13,608	\$ 1,655	\$ 7,246
Model 3	\$ 11,997	\$ 10,860	\$ 12,932	\$ 19,558	\$ 12,259	\$ 13,583	\$ 1,639	\$ 1,093

4.4.2 Sensitivity of utilization to time windows

As mentioned earlier, a pick-up and delivery time window is associated with each load. Higher flexibility, and hence wider time windows, has the potential to give more freedom in scheduling private/dedicated fleet. To analyze the effect of the time window on private/dedicated truck utilization, different time windows have been considered for each load. The flexibility has been applied according to the following equation:

$$Delivery\,time = Pickup\,time + (Travel\,time + Service\,time) * (1 + \%flexibility) \quad (4.19)$$

Analyzing the data for one depot shows that fewer Transportation, Inc. dedicated trucks can be utilized to carry the same number of loads when afforded wider time frames. In this condition, transportation providers can dedicate fewer assets to the customer without compromising the quality of service.

To further explore the sensitivity of time windows, Day 17 with 45 loads in all 3 depots were analyzed due to its high volume. Figure 2 shows that relaxing the time-frame by twice as much as travel time will result in the number of dedicated/private trucks utilized being

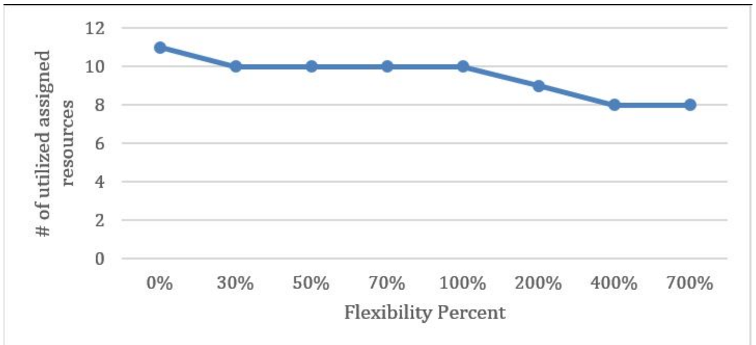


Figure 4.4: Effect of time window flexibility on required dedicated/private assets for one depot

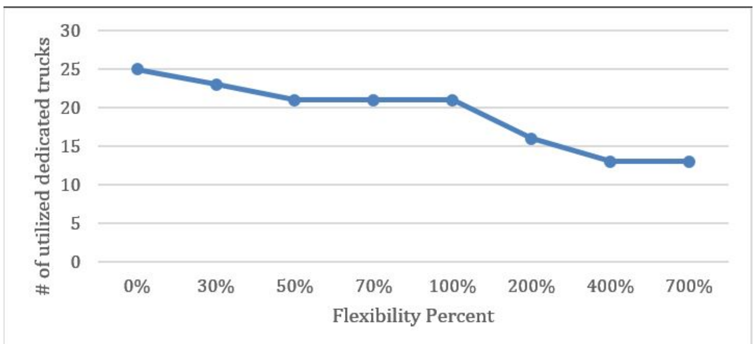


Figure 4.5: Effect of time window flexibility in 3 depots for one day

reduced by 36%. Each truck has a cost of $550 per day for maintenance, capital investment and overhead and reducing the number of dedicated/private trucks by nine will save the company $1,806,750 per year in contrast to the original 0% flexibility solution.

Relaxing this constraint was done to further illustrate the potential benefits of the proposed approach, as the original time windows were purposely conservative. This magnitude of this result was important to Transportation, Inc., as it identified an opportunity to consider wider and more flexible time windows in dedicated fleet contract negotiations where feasible, and it also shows that there are also other opportunities to reduce cost by influencing the time windows desired by customers. These results underlie the impact the model can realize as certain constraints are relaxed as part of a purposeful business strategy.

4.5 Discussion of Results

4.5.1 Theoretical implications

Even though the basis of the model presented in this paper is based on existing VRP and $VRPDP$ models, it adds to transportation fleet assignment and routing literature in a variety of ways. First, as Tab. 4.1 illustrates the existing models that do specifically address the daily assignment and routing of private/dedicated versus common carrier resources do so based on cost models that rely on direct costs. These cost models however, do not accurately reflect how Transportation, Inc. and many other private and dedicated transportation providers accrue costs when they are periodically assigning resources to customers or depots. This process makes the fixed cost of dedicated/private resources almost a sunk cost that is going to be incurred regardless of the trucks actually being utilized after the assignment decision. Thus, the cost model developed and described in this paper is a more authentic reflection of how these organizations are basing the dedicated/private resource versus common carrier assignment and routing decision in practice when assets can not be re-allocated as dynamically as the existing literature in Tab. 4.1 assumes. In addition to the updated cost model, the constraints in the model described above integrate VRP formulations for time windows ($VRPPDTW$) and carrier comparison ($VRPPC$) into a single formulation. Both of these are important factors that need to be considered in transportation models for the private/dedicated asset versus common carrier decision-making process [51]. To our knowledge, this is the first VRP formulation that allows comparison of dedicated/private versus common carrier resources for specific routes within time windows in a distribution network.

Finally, developing a cost minimization objective function using the updated cost model above along with$VRPPDTW$ and $VRPP$C constraints leads to the final contribution of this paper, which is the first known consolidation of the assignment and routing of private/dedicated versus common carrier resources into a single objective model. As illustrated in the results section, the solutions from this single objective model are improvements upon current multi-objective models that often rely on manual interventions and expert judgment. The ability to assign carrier type and pickup and delivery routing in a single objective model thus adds to the available academic models for a decision in which firms prioritize the utilization of increasingly scarce transportation resources at their disposal.

4.5.2 Managerial implications

A model that can be used by practitioners to assign and route a mixture of private or dedicated fleet with common carriers in a manner that reflects the actual decision-making criteria they value has numerous managerial implications. The most obvious is the elimination of the gap that pushes many organizations to manually intervene and manipulate the solutions generated by the automated models currently available to them for this process. These decisions can many times be required multiple times per day, and relying on decision processes that require manual intervention or being solved in a multi-objective manner can greatly inhibit the efficiency, and many times the effectiveness, of the assignment and routing process. The results illustrate how a single objective model that considers cost in a consistent manner to how firms in practice are making the decision along with a set of constraints that integrates two VRP formulations that are needed to properly frame the problem can compete with and even improve a multi-objective approach similar to how Transportation, Inc., a major logistics provider, was addressing the problem in practice.

In addition to savings on a transportation network, this model can also save transportation managers considerable employee time that is required to manually impose preferences for dedicated/private resources versus common carriers for shipments in a distribution network.

The practical implications of this approach are now being illustrated through a software tool that Transportation, Inc. developed and commercially launched in the summer of 2015. The tool is based on the model presented in this paper, and is a commercial software tool that works within an existing transportation management system to automate the assignment and routing decision for providers that utilize a mixture of private/dedicated assets and common carriers. The company describes the tool as an avenue to allow "customers (to) make better transportation decisions and save money by analyzing the best combination of transportation modes at the lowest total network cost in real time, load by load, every day", and that "Transportation, Inc. is the first transportation and logistics provider to offer this kind of automated capability". The benefits to customers are a tool that can be used to assign and route shipments in a manner that "consider(s) a number of other factors, such as available capacity and drivers, fixed fleet costs, and backhauls, automatically calculate(s) the true lowest network cost". Transportation Inc.'s implementation of the foundational elements of this model makes the managerial implications clear, as this model can provide practitioners an academic model that automates an increasingly common strategy in the transportation industry.

4.5.3 Conclusion, limitations and future research

While the model presented in this paper advances the literature, there are some limitations that must be considered and could be useful for extending the literature even further. First, evaluating the potential of a backhaul on a specific route was identified as an important factor in the dedicated/private asset versus common carrier decision process by Transportation, Inc. and other practitioners [51]. Including backhaul minimization in the model would require a separate dictionary of backhaul probabilities by route to include in the formulation of the model, but would further improve the decision-making process. A decision was made to not include this step in this current development stage, but Transportation, Inc. has since integrated this step into the next stage of development of their software tool. Additionally, this current model does not include any special equipment constraints for shipments that require specialized transportation assets, does not allow for the ability to pass shipments between depots in a single transshipment routing step, or allow dedicated/private assets to deliver multiple loads on a route. These conditions, while important, were not considered frequent enough given Transportation, Inc.'s existing business model to increase the complexity of the model in the initial development stage. Finally, the results presented are for one depot over a limited timeframe. Future research should include a larger set of shipments across numerous depots to more precisely estimate the impact of the model.

The ability to make the assignment and routing decision with the utilization of different types of transportation assets can also apply to other traditional modes such such as rail [79], but also new resources such as autonomous vehicles [80, 81] or Uber's crowd-sourced assets [82] to give them flexibility in their transportation network. The ability for firms to provide their transportation networks this flexibility through the utilization of new models that prioritize more relevant decision-making factors in a single objective model is even more critical in omni-channel distribution networks in which decisions must be made in compressed time frames across a variety of delivery lanes [83].

Finally, the current conversation in the literature between private and common carriage has focused primarily on the strategic decision for designing and sizing the private or dedicated fleet by a firm at periodic intervals [48, 84], as fleet sizing is a critical decision that affects transportation network performance [85]. This research has shown that an equally important decision in practice is the daily decision of assigning loads to either private/dedicated or common carrier assets once the private/dedicated fleet design has been fixed, as logistics flexibility through the effective utilization of common carrier resources can provide cost and service benefits [86]. However, the current models that make this more tactical decision have been shown to operate almost entirely upon cost minimization without taking into consideration the utilization, driver retention, and service requirements that also play an important part in this decision [87, 60]. Therefore, companies such as the research partner have had to use preference weighting methods, post hoc analysis, and even manual methods to fine tune the outputs of existing single objective cost models.

The current modeling approach is the first known effort to bring the dual decisions of asset assignment (common vs. private/dedicated fleet) and routing together into a single optimization model while allowing for other important criteria besides costs. For example, the vehicle assignment and demand allocation method using a coverage approach help firms achieve important side goals such as meeting government hours-of-service restrictions and returning drivers to their homes to help improve driver retention. In doing so, the model helps keep utilization of private/dedicated assets at a reasonable level in comparison to cost models that can radically decrease utilization of these assets to achieve relatively small cost savings. Overall, this approach prevents firms such as Transportation, Inc. from having to use multiple models or invest additional management resources in making manual adjustments to solutions generated by cost minimization models that do not consider the utilization, service, and driver requirements prioritized by their firm in practice. The model and research here has already had a significant impact on the decision-making and daily practices at a major logistics provider through the implementation of a new software tool whose foundation is the model presented in this paper. It is believed that ongoing and future research into this important decision-making area will help to improve the combined carrier selection and routing process going forward. While the cost and service priorities for a firm may change, the model presented here can be a foundation to solve the assignment and routing decision in a single objective based on factors other than direct cost as firms look to new types of resources in their future transportation networks.

5 Improved Green Supply Chain Performance Measurement Using Text Mining

5.1 Abstract

Measuring performances is an important aspect of supply chain management, and companies devote a considerable amount of resources to quantify and benchmark their performances. While most of the studies try to introduce new measures to assess activities, in the first part of this chapter, a method will be proposed to evaluate the resilience and efficiency of Key Performance Measures (KPIs) themselves. After being able to recognize the weaknesses and strengths of current performance measurement system, the gaps will be filled based on available standards. At the last step, environmental concerns will be addressed by adding green KPIs to the system, based on previous chapters findings.

5.2 Introduction

5.2.1 Overview

Performance measurement system or analytical framework of supply chain consists of two major parts a) measures b) connections. Having a comprehensive set of KPIs is crucial, and companies try to add KPIs to make sure that every aspect of performances and activities are covered. The first problem is that the companies add overlapping and parallel measures and spend time and money on analyzing overlapping, parallel and unnecessary KPIs. The second issue in most of the companies is that while there is a focus on developing and calculating measures, building hierarchical connection has been neglected. In this chapter, a text-mining based approach will be recommended to find the weaknesses of the current analytical framework in each company. On the other hand, there is available standard with recommended measures and structure. These frameworks do not reflect the expertise and uniqueness of the enterprise.

In this paper, a text analysis approach will be utilized to find the weaknesses of the current analytical system. The weaknesses and gaps will be addressed using available standards. After improving performance measurement system, energy and environmental KPIs will be added to the framework based on literature and previous chapters findings.

5.2.2 Problem statement

The objective of this study is to improve the analytical framework of any company by understanding the weaknesses of current performance measurement system and then, adding

Figure 5.1: Companies using SCOR

missing as well as environmental KPIs. Researchers and practitioners came together to provide a unique framework for supply chain measurement. The effort leads to a standard named SCOR [88]. SCOR recommended five core attributes: reliability, agility, responsiveness, cost and asset management. The core attributes will be broken down into lower level KPIs. SCOR's recommended structure has three levels of general KPIs and business measures go into lower levels. Level 1 metrics quantifies the overall performance of the system. The level 1 metrics also provide the opportunity of strategic benchmarking. Going to lower levels, metrics in each level are serving as diagnostic to the higher level metrics [88].

The SCOR framework is very useful and applicable and has been employed by many companies around the word. Companies like IKEA, Boeing, IBM are actively involved with using and improving SCOR. The Fig. 5.1 illustrates a snapshot of companies using SCOR around the globe [88].

Although SCOR is a powerful tool, every company has its uniqueness. Different companies have different KPIs with various hierarchical structure. The structure, measures, and weights can be affected by:

- *Business strategies:* strategies can change over time. At some point, a company might focus on getting a higher market share and consequently less financial concerns. This strategy puts more weight on sales KPIs. The policy may change in future years, and another KPIs like economic benefit becomes important.

- *Organization structure:* the structure and size of a company are other factors [89]. Small businesses with a few layers of management need fewer hierarchical levels in performance measurement system compared to a bigger company. The relation between managerial and KPI hierarchy will be discussed more in the paper.

- *Customer needs:* total quality management (TQM) connected quality to customer satisfaction, and different costumes have different criteria [90].

- *Carrier relation*: Different types of contracts with carriers and different carrier selection strategies will result in different KPIs.

These are a few parameters—more can be listed—that can cause a difference in analytical frameworks among companies. On the other side, companies tend to add KPIs over time, without having a tool to test necessity of new KPIs.

In this paper SCOR has been modified by adding the following capabilities:

- Estimation of the effectiveness of current KPIs.

- Finding the gaps and weaknesses in the current analytical framework.

- A systematic approach for the testing necessity of any recommended measures.

- Estimate the impact of the supply chain on the environment.

5.2.3 Related literature

To have a robust analytical system, we have to define the characteristic of a resilient and effective measurement framework. An efficient analytical system can provide us with not only a system of performance measurement but also with a structure of information sharing. An analytical system can also powerfully reduce inefficiencies in processes and increase alignment. The following characteristics are the most important aspects of a well-defined analytical system:

- Hierarchical structure: having hierarchical relation between KPIs is the main feature of a sound analytical system. The following are the main benefits of this structure:

  - Cascading strategies throughout the company will be systematic [91]. Using hierarchical structure, policies can easily be followed to activities. The most efficient actions for implementing strategies can be targeted, and new benchmarks can be set.
  - Cause and effect analysis will be simply done based on hierarchical relations [92].
  - Different levels of management will have a handful of specific KPIs to check and weight based on policies. As an example CEO needs to weight 5-6 high-level KPIs, in the next hierarchical level each EVP will adjust the weights of a manageable number of branches based on higher level strategy. The process of implementing strategies and policies will be more manageable, straightforward and short.

- Modification process: companies tend to change their KPIs over time. They mostly add a measure
  - In revising KPIs, there should be a balance between experience and theory.
  - There should be a systematic approach for measuring the importance and necessity of add/remove candidate KPIs.

- Allow for setting target: a hierarchical setting lets us to set targets or benchmarks at different levels of decision-making (strategic, tactical, and operational) [93].

- Information sharing mechanism: as a side product, the analytical structure should recommend an exchange of information tool [94]. The purpose of data collection should be clear and necessary variables should be collected and shared between departments.

Having a hierarchical structure is the first part that has to be investigated to answer the question of: "How good is a performance measurement system?".

To find the hierarchical structure, different relationships have to be defined. Cai *et al.* defined the following relations for performance measures [95]:

- Parallel: when two KPIs are entirely independent and improving one does not have any impact on the other.

- Sequential: when two KPIs have cause and effect relation.

- Coupled: two KPIs are dependent on each other in both ways.

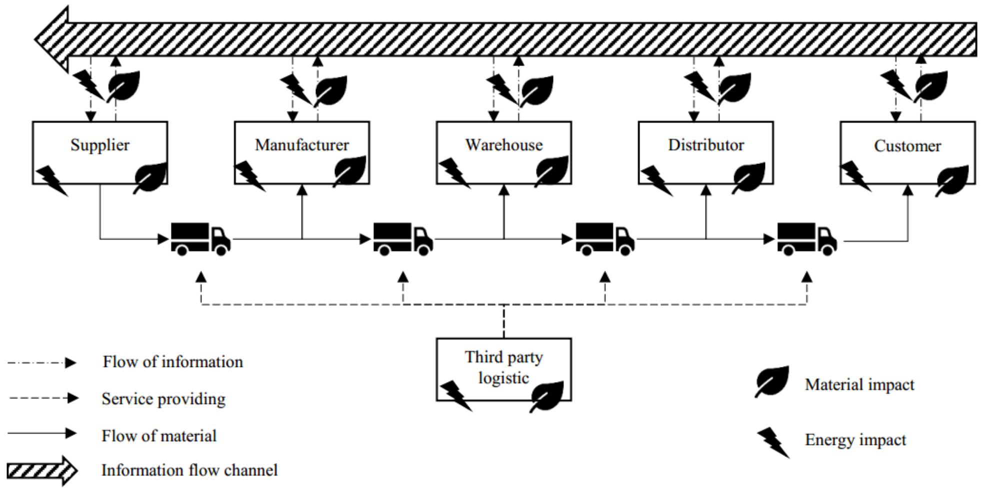


Figure 5.2: Influence of supply chain on environment

In order to find the structure and relations, researchers recommended different methods including survey [95]. But in a single and small company, the number of respondents and their point of views are limited, and survey cannot be reliable. In this chapter, a text mining approach has been recommended to find the relation between KPIs. After the relationships and gaps are obtained, the gaps will be filled using SCOR, as a widely utilized analytical approach.

After being able to assess the current KPIs, environmental measures will be recommended to be placed in the correct position in the hierarchical structure. In academia, KPIs developed for a green supply chain but not being widely used in day to day measurements because they require technical knowledge about environment, materials and electricity market. On the other hand, some of the approaches are not compatible with standards like SCOR.

Sarkis discussed how different parts of the supply chain have a negative impact on environment [96]. Sarkis did not consider distribution and transportation in his model.

Defra [97] considered four key categories for pollution a) emission to air b) emission to water c) emission to land d) resource use. Recardo-AEA showed that different factors could have an adverse impact on the environment in one of the following ways [98]:

- Global warming potential: Global warming is the term to address the rise in trend in the Earth's climate system average temperature. Generated amount of CO_2 can measure the impact of process on global warming.

- Acidification potential: Acidification is referring to decrease in ocean's PH. Generated $H + moles$ can quantify the impact of the industrial process on acidification.

- Eutrophication potential: Eutrophication refers to depletion of oxygen in the water which results in the death of underwater creatures. Generated N can be a measure for eutrophication.

- Ozone depletion potential: The amount of generated nitrogen oxides (NO_x) quantifies the impact on ozone depletion.

- Smog formation potential: Trichlorofluoromethane ($CFC - 11$) is the main source of smog formation.

- Human health impact: The effect of materials on human life should also be measured.

Beamon considered the state of the environment as a) solid and hazardous waste b) water and air pollution. He also discussed public pressure and image of the company [99]. He also stated that manufacturing operations would pollute the environment through following categories:

- Waste

- Energy use

- Resource use

These measures are hard to calculate and requires different expertise. Some researchers recommended going toward simpler measures and using ANP, DEMATEL ... [100, 101]. In this chapter, we proceed with activity-related measures instead of impact oriented.

In the rest of chapter, first, we try to introduce a method for collecting current KPIs, then based on a text mining we find the relationship between KPIs. The current KPIs will be improved to make a performance measurement system instead of having a set of measures. A case study will demonstrate how the suggested approach works in a company. In the last section of this chapter, environmental KPIs will be added to the system.

5.3 Methodology and approach

In this study, text mining will be utilized twice. First to understand the hierarchy and structure of KPIs and then to find out the relative importance of each measure. Finally, a set of environmental KPIs will be added to the model based on previous works.

5.3.1 Data collection and standard formulation

Differences in company policies and structures in addition to different customer requirements result in different KPIs. This unique experience which led to a unique set of performance measures is a valuable asset and has to be considered. To find the effectiveness of current KPIs, all measures have to be collected and calculating formula should be obtained. To avoid any confusion, variables (process attributes) has to be defined clearly to the lowest necessary detail (performance attributes). The name of variables will be as follows:

- D: Variables related to delivery
- P: Planning variables
- S: Source variables
- M: Variables related to making process
- R: Return process variables

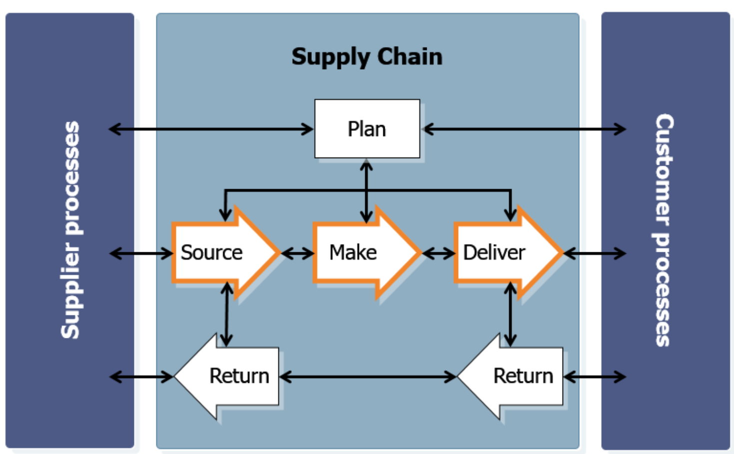


Figure 5.3: Supply Chain

The variable names have been adopted from SCOR. After the variable has been defined, each KPI has to be formulated in the following standard way:

- Variable definition: It is not allowed to formulate a KPI based on another KPI. This idea avoids unnecessary variables to enter the system and prevents defining the same KPIs with different names in different levels of calculation.

- Operators: A formula can be defined in different ways, to avoid inconsistency, the following rules are recommended:
  - Use *sum, count, in {}, +, **. Use / only for percentage and portions.
  - Avoid using other operations as much as possible (- , *except, not in {}*)
  - Use a "cluster by" column if the variable is clustered by an attribute (customer, region, . . .). A sample of the standard formulation is shown in 5.1.

An example can shed light on the procedure of formulating measures. Consider a company with two type of carriers: internal and outsourced. $D.1.$ is 1 if the private fleet has been utilized and 2, 3, 4 for different outsourced carriers. There are five different customers with different labels on the product. Variable $M.1.$ will separate them by assigning a number (1,...,5) to each customer. $D.2.$ saves the mileage for each trip.

"Mileage traveled for each customer by outsourced fleet" will be formulated as:

$$sum(\, D.2.\ if\ \ D.1.\ in\, \{2,3,4\}\,)\, cluster\, by\, M.1. \tag{5.1}$$

Each formula can have three types of variables:

- Main variable: is the operand variables. A formula may have more than one main variable.

- Subset variables: not all values of the main variable will be considered in the formula. In most cases, a subset of the main variable will be considered based on the value of another attribute. For example, to calculate the average cost of shipments (shipment cost attribute), we only consider delivered loads (delivery status attribute).

- Cluster variables: some measures has to be calculated for all subsets of another variable. For example, the cost has to be calculated for each customer separately, which makes customer ID a cluster variable.

As an example, in 5.1,

- $D.2.$ is the main variable with freq. of 1
- $D.1.$ is the subset variable $D.1.2$, $D.1.3$, $D.1.4$
- $M.1.$ is the cluster variable

The variables and formulation can help us find the relation between KPIs. KPI relation can be defined based on formulas as follows:

- Parallel: KPIs without common variables with the same frequency are completely parallel.
- Sequential: variable A is sequentially related to variable B if
  - All main variables of A are in B with the same frequency
  - All subset variables of B are in A (considering empty set)
  - Clustering variable of B is in clustering variable of A
- Coupled: KPIs using the same set of variables with the same frequency are considered to be coupled.
- Overlapped: some variables are shared between KPIs

In calculating Overlapped KPIs, higher weight has been assigned to main variables in comparison to subset variables. We would like to have no parallel KPIs, not many overlapping KPIs and all KPIs to be in a sequential relation. Preliminary steps showed that operation (sum, count, ...) do not have any impact on the results since operands are logically associated with a specific operation. As an example, traveled miles always will be used by *sum* and operand will not provide any extra information.

5.3.2 Importance of measures

So far, the relationship between KPIs has been obtained. The previous step shows how different KPIs are connected and how much new information each KPI carries. In this step, we want to distinguish between important measures and nonimportant measures since each metric cannot be a key metric.

Important measures are being communicated more among supervisors and managers. Based on this assumption, researchers can analyze the emails and minutes of meetings using text mining and use repetition of each measure in addition to information delivered by it to estimate the importance of a KPI. The words with higher repetition are assumed to be more important. More important measures have a higher chance of remaining in the system.

The importance of each KPI (kpi_imp) can be measured by:

$$kpi\_imp = rep\_sc * info\_sc \tag{5.2}$$

where rep_sc stands for "repetition score" and $info\_sc$ stands for "information score". Repetition score measures the relative usage of each KPI in communications (from 0 to 1), compared to other KPIs. Information score measures how much information each KPI carries. Information score considers the amount of information that is not overlapped with the information from other KPIs based on text analysis of formulas.

5.3.3 Adding environmental KPIs

SCOR has 5 level 1 metrics, environmental measures can be the 6$^{\text{th}}$ one. As discussed earlier, we are looking for a performance measurement system that laser points the required activities, starting from highest to lowest level. Based on different activities in a supply chain, the first level can be defined as design, procurement, manufacturing, packaging, distribution and reverse logistic.

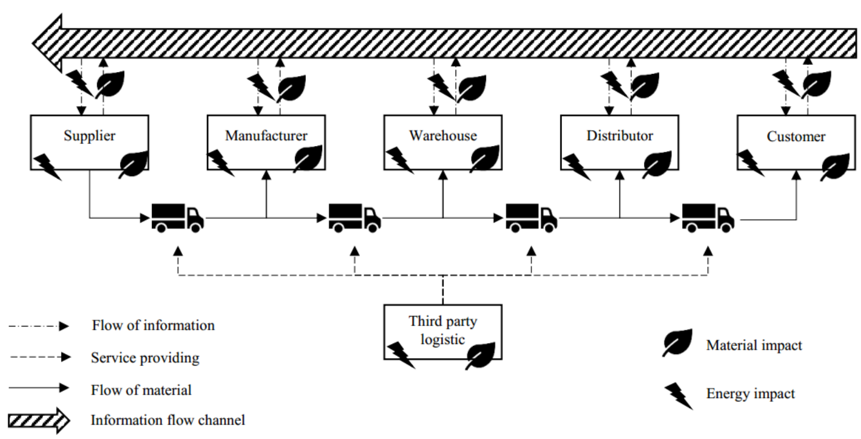


Figure 5.4: Recommended level 1 metrics

Design and planning: Design and planning have similarities that result in the same KPI structure although the measures have to be calculated differently. The main environmental indicators are material and energy related measures.

- Material: Type of used material are a decisive factor. Some part of material can be reused or reprocessed, but a part goes to disposal because of weak design or lack of reverse supply chain or infrastructure. The disposed material can have a negative effect on the environment in terms of global warming, acidification, eutrophication, ozone depletion, smog formation or human health [98].

- Energy: Energy consumption in design and planning can be considered as:
  - Energy per item: this measure considers energy including startup energy, setup energy, direct energy and environmental energy (HVAC, light) [39, 102].
  - Demand response potential: participating in demand response can be in terms of changing demand due to changes in electricity price in power market or receiving incentives and shifting loads based on a contract with the utility company. Availability of planning tool which considers energy is the first step for DR participation. Theoretical potential of participation in demand response is the measure of DR participation.
  - Energy source: different energy sources can be considered and utilized for production. As an example, a furnace can be operated by coal or electricity. Percent of clean energy sources can indicate how well a company is doing in this area.

Procurement: Procurement has a significant part in going green. The following steps show how different measures can quantify environmental performance of procurement:

- Paperless purchases: by using ERPs, EDI and ... procurement can go paperless. Percentage of paperless transactions can be the measure.

- Supplier selection: supplier selection is a big part of procurement and companies try to contract reliable suppliers. Giving priority to suppliers with ISO 14000 series can guarantee that suppliers have environmental concerns and meet minimum standards [103].

- Electricity sourcing: Finally, power market provides the opportunity of bilateral contracts for electricity supply. Contracting renewable resources in electricity market can support environment. Percent of bilateral renewable contracts can be a good measure for this section.

Manufacturing: The impact of manufacturing on the environment can be quantified as wasted materials and energy as follows:

- Energy:
  - Energy per item: the real energy consumption can be compared with design and planning.
    - Working energy: energy during production as discussed in chapters 2 and 3.
    - Start-up energy: energy after the machine is started and can be higher than nominal power as described in chapters 2 and 3.
    - Set-up energy: as discussed in chapter 3, set up activities can consume energy.
    - Idle energy: total energy consumed during idle times.
  - Indirect energy: this part is related to HVAC, light and any other segment that does not contribute to production.
  - Inventory: overproduction causes storage cost as discussed in chapter 3.
  - Demand response participation: percent of shifted demand can be compared with planning demand response potential.
- Wasted materials: as in design section, wasted material can have an impact on the environment in terms of global warming, acidification, eutrophication, ozone depletion, smog formation or human health [98].

Distribution: With simplification, distribution can be considered as warehousing and transportation with different measures in each section.

- Warehousing: the amount of energy used for warehousing of each item can indirectly measure the impact of warehousing on the environment.
- Transportation: different transportation modes produce different levels of CO_2 emission [104]. Consequently percent of loads transported by each mode (road, rail, air, marine) can indirectly capture the impact on the environment.

- Road: development of hybrid and electric trucks requires more focus on this mode. Percent of road loads carried by hybrid, electric, fuel operated trucks can measure the environmental impact of road transportation better.
    * Percent loaded miles: avoiding empty miles is the main strategy for reducing fuel. This concept has been discussed in chapter 4.
    * Fuel consumption per loaded miles: some companies measure fuel cost, which cannot reflect the real impact on the environment because of fuel price volatility.

Reverse logistic: In reverse logistic, transportation mode and warehousing become important again and can be measured the same. The percentage of materials not returned to the process has to be considered based on their impact on the environment and human health as a kind of a waste.

5.4 Case study

The case study has been performed in a food and beverage production company. In the company, supply chain department is strong in measuring performances, and 204 of its KPIs were analyzed from 24 different reports. Using Python coding language, a model were developed to analyze the relation between KPIs. The model found 16 pairs of coupled (redundant) KPIs in different reports. Also, 79 sequential relations have been found with most being only two and three element links and 129 KPIs are either completely isolated or have overlapping relation with others. For perspective, in a robust KPI structure, most operational KPIs should have 4-6 levels of KPI linkage. Results show that supply chain department has many unconnected low-level KPIs (in performance measurement level) and not enough connecting (Aligning) KPIs. The linkage and relation show the KPIs are not connected, and consequently strategies will not cascade throughout the company effectively.

In terms of green KPIs, the only related measure is the fuel utilized for delivering the load in the logistic department and wasted material in production. These two KPIs has been considered not because of environmental concerns but for their impact on cost.

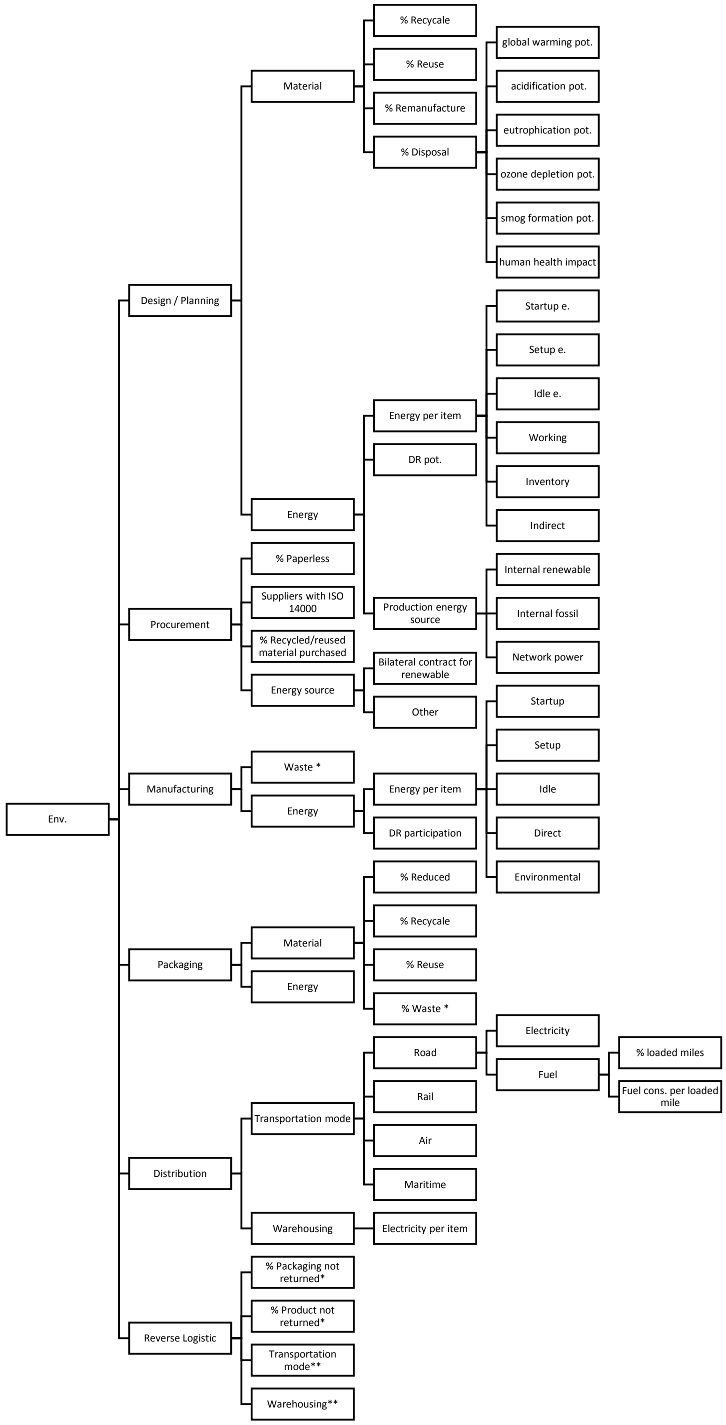


Figure 5.5: Environmental KPIs
* can be analyzed in smaller segments: design →material → disposal
** can be analyzed in smaller segments: distribution →transportation mode

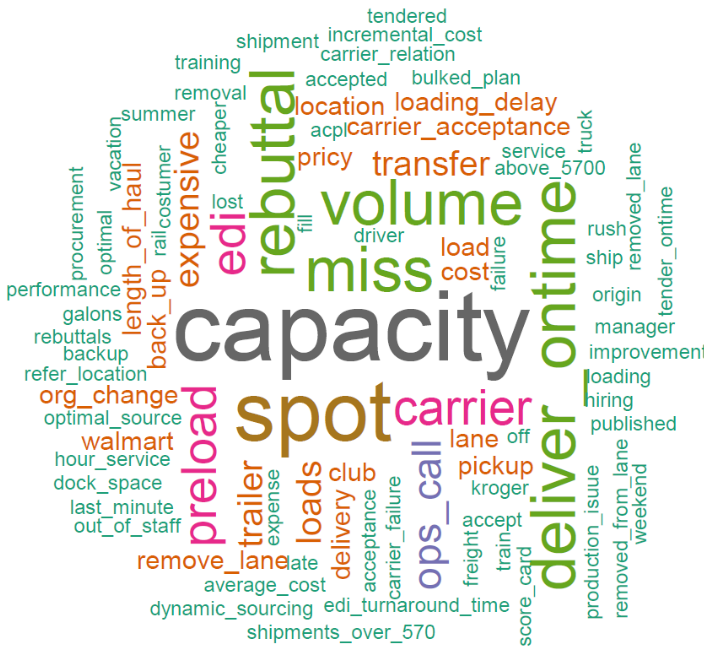


Figure 5.6: Word cloud of meetings

5.4.1 Adding and removing KPIs

In terms of traditional KPIs, the current system has weakness in the connection between KPIs and has so many isolated KPIs and overlapped measures. Therefore, some KPIs have to be deleted and some have to be added. Managers talk about important measures in their meetings. Text mining has been used to analyze minutes of meetings. KPIs related to highly used words has been considered to stay in the model.

Some performance measures have been clustered (by the customer then lane then ...) in many levels. After the first level of clustering (cluster by variables), further breakdowns are considered to be too detail and not worthy of calculation as a *key* metric. The connecting KPIs which stand in the middle of hierarchical structure has been added using SCOR.

5.5 Conclusion

In this paper, text mining has been utilized in two levels to measure the effectiveness and robustness of supply chain performance measures. A systematic approach has been recommended and tested to examine the measures and put them in a hierarchical structure based on available standards. The method has been tested in a company and relieved the weaknesses of the current analytical landscape. The companies tend to change their measures and KPIs. The recommended model can also be utilized to check the necessity of newly recommended KPI and prevent unnecessary measures to enter the system.

In addition to that, a new level 1 metric has been added to SCOR as *Environmental,* which can measure the impact of the supply chain on the environment. The recommended structure and measures are more complicated in design and planning and simpler for tactical measures. This will help day to day measures to be understandable for employees on factory level and more complex for designers with higher knowledge and education.

6 Conclusion

6.1 Dissertation conclusion and discussion

As discussed in Chapter 1, the US has done a significant amount of work to control and reduce the amount of environmental pollution. While the amount of CO_2 emission in the US has been stabilized in the recent decade, the further statistical analysis shows the US is still among "high polluting countries." The study shows the most efficient targets for emission reduction are transportation and industrial loads. In this dissertation, we focused on electricity consumption in manufacturing and fuel consumption in transportation in the context of the lean supply chain.

Traditional manufacturing had the tendency toward large batch sizes; this strategy is simpler to operate and manage and was assumed to be more efficient [105]. Despite this assumption, Toyota Production System (TPS) suggested that the large lot size has a negative impact on lead time, inventory cost, flexibility and quality [105]. The new concept of lean motivated companies around the world to adopt "small lot sizes production" to gain the competitive advantage in the market. Small lot size leads to more set-up changes on machines. There is a considerable amount of work dedicated to set-up time reduction in lean literature, while the impact of set-up changes on energy and transportation received less attention.

In a production line, increased number of set-up changes will lead to high rate of partial or complete line start-up. In transportation aspect, the higher set-ups and small lot sizes provides a more diverse set of products in sales level and would result in more frequent deliveries.

The impact of small-lot size on manufacturing has been investigated in chapter 2 and 3. Identifying the states of energy consumption is the first step toward managing the energy. In most of the manufacturing devices, especially in subtractive manufacturing and material removal processes, motors are the primary part of the machines. Based on this fact and the importance of start-ups as consequence of small lot size, in the second chapter, we focused on characteristics of motors during start-ups. Different types of motors have been analyzed in this section, and the impact of start-ups on increasing power consumption have been discussed. In this chapter, we introduced a method for measurement of energy consumption in manufacturing devices. The emphasis was on start-up power consumption, and a regression-based model has been introduced to simplify the measurement of energy consumption. A MATLAB based energy simulation and visualization tools have been developed in this chapter. The cases studies and simulations show that unit one lot size can increase the power consumption significantly (even more than 10%).

The second chapter laid the groundwork for more advanced production planning. In the third section, we added different states of direct energy consumption (working, idle, start-up) in addition to indirect energy consumption (set-up, inventory holding) to production planning. A design of experiment has been employed to assess the impact of different factors on shifting loads between hours to take advantage of lower price electricity. Based on the DOE, line utilization and start-up time are the significant factors that determine the involvement of production facilities in demand response programs.

Chapter 2 described how energy consumption during start-up can change the concepts of lean and small lot sizes. In the third chapter, opportunity of demand response participation and taking advantage of lower electricity price has been considered. In the new paradigm of manufacturing, with variable electricity price, start-up time is another important factor. Based on chapter 2 and 3, the energy consumption during start-up as well as start-up time plays a crucial role in energy efficient production planning.

The utility company and electricity market can also benefit from the results and approach of the chapter. While estimating the participation of consumers in DR programs in literature is based on quantity-price models from economy papers which do not reflect the complexity of costumer's decision-making in the electricity market, the introduced model and DOE can provide a complete bottom-up analysis with a more accurate distribution of load change. The introduced distributions can help researchers in stochastic analysis and utility companies in estimating the load variations in the market.

The first model in chapter 3 shows that companies with high utilization of production line do not have enough flexibility to shift their loads and participate in DR. Therefore, another model was developed which is capable of moving some part of load to the second shift to take advantage of lower electricity price of afternoon with compromising labor cost. The results show that in the case of high production line utilization, manufacturers can benefit from real-time pricing in the energy market by running a second shift.

With small lot size, a more diverse product mix will be available at shop floor which leads to increase in the frequency of delivery. The higher and more complex delivery rates happen while transportation is considered as a waste in lean literature. The situation becomes even worse when we consider a lot of reported empty miles. In the fourth chapter, we consider a combination of private/dedicated carriers with global/common carriers to reduce empty miles and variable cost of fleet operation.

The recommended cost model and decision-making tool results in a lower variable cost of trips and consequently the lower fuel consumption. The model solves the vehicle routing problem and carrier selection in one step which guarantees global minimum and removes additional steps in the decision-making process. A dimension reduction approach has been recommended which cuts the solution time considerably.

At the last step, we need to remember that unmeasured activities are at risk of downfall. The reduction in electricity, participation in demand response and fuel consumption should be measured to avoid backsliding. A resilient KPI system not only has measures but also provide a hierarchical relation between measures. In the fifth chapter, first, a text analysis method has been introduced to find the relationship between current KPIs in a company. Then using SCOR, the gaps in hierarchical relation has been filled, and environmental measures have been added based on previous chapters' findings. The proposed method can evaluate the effectiveness of currently developed measures in a company and also assess the necessity of newly recommended KPIs.

6.2 Future work

The present study provided a new perspective on energy management in supply chain, offered new means of energy measurement and minimization in forms of simulation toolbox, mathematical model, and performance measurement tools. However, there are a vast amount of research potential in the area of Lean and Green supply chain.

- The future research can consider the methods developed in chapter 2 for heating process, ovens and furnaces since they are good candidates due to long warm-up (as a kind of start-up) and heavy working and idle energy consumption.

- From a production planning perspective, the states of energy consumption can be considered in a more specific optimization model since the recommended approach is a general model.

- In the third chapter, DOE has been employed to find the elasticity of demand in Real Time Pricing electricity market. There are many other demand response programs (like time-of-use, incentive based) that can be tested with the introduced production planning models and DOE to find the elasticity of load change.

- The umbrella constraint detection in the fourth chapter has a tremendous potential, and hopefully, researchers apply this method in various large-scale problems to reduce size and solution time. The recommended partial run of UCD in addition to relaxing binary variables makes the Mixed Binary Problems much faster, and the model can be applied in wide range of problems including Unit Commitment and Transportation.

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