ALTERNATIVE TRUCK TECHNOLOGY: STRATEGY AND POLICY RESEARCH BASED ON MULTI-STAGE STOCHASTIC PROGRAMMING

A Thesis

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Master of Science

by

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ABSTRACT

A multi-stage stochastic programming model is formulated to provide suggestions for logistics companies in purchasing and selling truck fleet inventory. To deal with the uncertain nature of several parameters such as productivity, scenario-based nonanticipativity constraints are introduced. Further, this study presents computational results of a specific case to check feasibility of the model, using *cplex* optimization package in AMPL. To discuss the function of several current policies, more cases are constructed and solved. This study makes corresponding suggestions concerning new energy vehicle incentive according to model solutions. Currently there is little incentive to purchase electric trucks (E-trucks), but under certain policies such as rebate, E-trucks are strongly favored.

Keywords: Multi-stage Stochastic Programming, Electric Truck, Logistics, Supply Chain, New Energy Vehicle Incentive Policy

BIOGRAPHICAL SKETCH

The author, Boyu Wang, was born in Qinhuangdao, a beautiful coastal city of China. He spent 18 years in his hometown, from elementary school to high school, and gradually developed strong interest in science and engineering, especially at his high school, Qinhuangdao No.1 High School. Boyu was admitted to Tongji University in Shanghai, China at 2010. During his undergraduate study, he gained solid background and skills in his major, transportation engineering. In Summer 2013, he went to École Polytechnique Fédérale de Lausanne (EPFL) in Switzerland as an exchange student and spent six months there. The exchange experience rendered him with a determination to pursue for higher degree. After he earned his Bachelor of Engineering degree from Tongji University, he was admitted to the Master of Science degree program in Transportation System Engineering at Cornell University in Fall 2014. He studied there in the following two years with the company of the gorgeous scene of Ithaca.

This thesis is dedicated to my parents: Hu Wang and Yuhua Li

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

The basic goal for a logistics company is to deploy a sufficient truck fleet to certain locations so that the transportation demand is satisfied. Thus the inventory for a logistics company is their fleet of trucks. Therefore, unlike regular agent that conduct business of making and selling items like cellphone, truck inventory of logistics company is largely determined by the transportation network where the logistics company serves as well as its own productivity. Meanwhile, trucks also share similar characteristics with regular business goods, which indicate their inventory planning also depends on parameters such as purchasing price, selling revenue and holding cost. The uncertainty over time, however, makes inventory optimization difficult. Loss of vehicle value due to depreciation with time is significant and depreciation is always stochastic. Another critical parameter productivity, which in this study is defined as the expected mileage a truck can run per year, is also stochastic.

New technology to reduce transportation emission and improve truck productivity has been emphasized by not only the scientific community but also government. The 21st Century Truck Initiative (21T) (Misener, James A., and David J. Gorsich ,2000) combined government, industry and academic interests in improving fuel efficiency, reducing emissions, increasing safety and reducing the cost of ownership. (*1*). A non-profit organization *CALSTART* delivered a detailed report about E-Truck Task Force, in which they found E-trucks are capable of reducing cost while maintain same level productivity as diesel trucks. Moreover, the cost of E-trucks is expected to drop continually in the following five years (*2*). The development and application of new energy commercial vehicles such as hybrid electric vehicle (HEV)/electric vehicle (EV) makes it possible for logistics companies to use them and hence save cost. The possibility lies in the trade-off among lower emission cost, higher purchasing price, incentives for electric trucks (E-trucks) and slower productivity reduction in comparison with diesel trucks.

Considering all factors above, it is critical for a logistics company to have an optimal truck operation strategy to ensure there is sufficient supply and to minimize the total cost. Therefore, this study formulates a scenario based multi-stage stochastic programming model for truck purchases and sales. Specifically, all vehicles are assumed to be brand new at the first stage/time period.

Mixed-Integer Programming

Mixed-Integer Programming (MIP) is widely applied to solve industrial operation planning problems. With all decision variables constrained to be integer, MIP guarantees the feasibility of optimal solutions. Tom Schouwenaars et al. (2001) presented MIP to solve fuel-optimal path planning of multiple vehicles using combination of linear and integer programming (3). Mark Kuchta et al. (2004) introduced MIP to implement a production schedule at LKAB's Kiruna Mine to optimize deviations of production quantities with operational restriction (4). Erkan Tapol et al. (2011) further reduced the number of variables in MIP to improve the model's ability to generate optimal results (5). To deal with stochastic situations in MIP, Erkan Tapol et al. (2012) created a stochastic based MIP with objective functions to minimize the maintenance cost for truck fleet. They simulated 21 scenarios, one of which is a base case to estimate maintenance costs, and they solved remaining 20 scenarios using the base case (6). Their study presented the possibility of combining mixed-integer programming and stochastic programming.

Multi-stage Stochastic Programming

In Operation Research area, there are two kinds of mathematical programming:

1. Deterministic mathematical programming where the input data/parameters are known;
2. Stochastic mathematical programming where the input data/parameters are unknown but it is possible to determine their statistical distribution.

Due to common uncertainty in reality, stochastic programming is often a better reflection of industry problems. Furthermore, a valid and functional methodology multi-stage stochastic programming (MSP) can be introduced to present the dynamics of system, especially when the system has an uncertainty nature. Related research of MSP is pretty sufficient. Dupačová *et al.* (2000) discussed scenarios and scenario trees of multi-stage stochastic programming explicitly (*7*). For a multi-stage stochastic process over a finite time horizon t = 1…T, denote $\omega^s \in \Omega$, where $s = 1 \dots S$ as scenarios set with discrete probability distribution of each scenario P^s ($\sum_1^S P^s = 1$). To realize this, introduce a vector decision process (a vector of decision variables)

$$x = \{x_1^s, x_2^s, \dots, x_T^s\} ,$$

Therefore, a general multi-stage stochastic programming could be formulated as:

$$min/\,max\, F(x, \omega)$$

Subject to:

$$h_i\,(x, \omega) \geq 0\; \forall\, i$$

However, for a multi-period problem with *T* time horizon, even if it is possible to determine a valid decision of time *t*, it is often the case that information is not sufficient enough to make decision for *t+1*. Therefore, to get sequential decisions in time, Flam *et al.* (1985) introduced a so-called *non-anticipativity* constraints (*8*). Abel A.Fernandaz *et al.* (1996) discussed the impact in multi-period stochastic programming of omitting non-anticipativity constraints, one of which is the solutions respect physical but not temporal constraints (*9*). N.C.P Edirisinghe *et al.* (1999) provided an elaborate interpretation of multi-stage stochastic programming with nonanticipativity constraints

(*10*). Suppose there is a decision variable ***X*** with scenario index $s \in S$ and time index $t \in T$. Due to insufficient information, those scenarios share the same characteristics before the incoming information enables them to be separated from each other. Suppose before time period ***t***, all decision variables ***X*** are identical:

$$x_1^{s1} = x_1^{s2} = \cdots = x_1^{s}$$

$$x_2^{s1} = x_2^{s2} = \cdots = x_2^{s}$$

$$\ldots$$

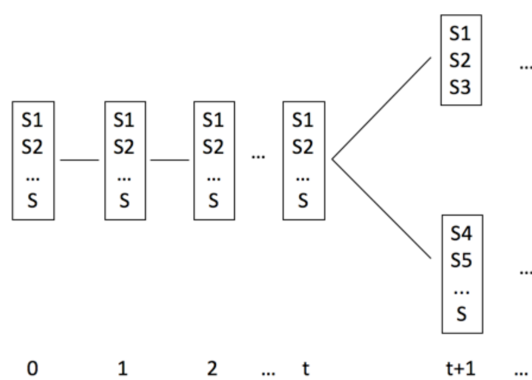
$$x_t^{s1} = x_t^{s2} = \cdots = x_t^{s}$$

Suppose at time period *t+1* some scenarios become distinguishable from others, say s1, s2 and s3, then the additional constraints are:

$$x_{t+1}^{s1} = x_{t+1}^{s2} = x_{t+1}^{s3}$$

$$x_{t+1}^{s4} = x_{t+1}^{s5} = \cdots = x_{t+1}^{s}$$

The nonanticipativity constraints formulation can be described by following scenario tree graph:



The scenario tree enables the multi-stage stochastic programming to be solved by appropriate optimization solver.

CHAPTER 2

MODEL FORMULATION

This model is dedicated to providing instructions for a long-term truck fleet operation strategy in a specific geographical area under uncertain truck productivity. Based on traditional transportation network optimization, several decision variables are introduced to represent critical dimensions of the truck fleet inventory. These variables are purchasing number, selling number and total inventory. This study includes dimensions such as time, vehicle type and scenario to make the model capable of dealing with long-term and uncertainty. Since the productivity of trucks will decrease along with time, corresponding parameters and decision variables should have two indices regarding time; one is initially purchased date and the other is present time. Besides this, they will also need a scenario index.

Figure 1. Model Indices

$\boldsymbol{i} \in \boldsymbol{I}$: Denotes a demand site

$\boldsymbol{j} \in \boldsymbol{J}$: Denotes a demand site

$\boldsymbol{k} \in \boldsymbol{K}$: Denotes truck type

$\boldsymbol{t} \in \boldsymbol{T}$: Denotes the time period

$\boldsymbol{w} \in \boldsymbol{W}$: Denotes the initial purchasing time period

$\boldsymbol{r} \in \boldsymbol{R}$: Denotes a scenario regarding productivity

Figure 2. Decision Variables

$\boldsymbol{N_{w,r}^{k}}$: Total number of newly purchased type $\boldsymbol{k}$ trucks at time $\boldsymbol{w}$ in scenario $\boldsymbol{r}$

$\boldsymbol{S_{w,t,r}^{k}}$: Total number of type $\boldsymbol{k}$ trucks purchased at time $\boldsymbol{w}$ and sold at time $\boldsymbol{t}$ in scenario $\boldsymbol{r}$

$\boldsymbol{Y_{w,t,r}^{k}}$: Inventory of type $\boldsymbol{k}$ truck purchased at time period $\boldsymbol{w}$ at and held at time $\boldsymbol{t}$ in scenario $\boldsymbol{r}$

$\boldsymbol{x_{i,j,t}^{k}}$: Empty trucks from site $\boldsymbol{i}$ to site $\boldsymbol{j}$ at time period $\boldsymbol{t}$

$\boldsymbol{y_{i,j,t}^{k}}$: Fully loaded trucks from site $\boldsymbol{i}$ to site $\boldsymbol{j}$ at time period $\boldsymbol{t}$

Figure 3.Model Parameters

$\boldsymbol{c^{f}}$: Transportation cost of fully loaded trucks, \$/truck/mile

$\boldsymbol{c^{e}}$: Transportation cost of empty trucks, \$/truck/mile

$\boldsymbol{C^{k}}$: Emission cost of a type $\boldsymbol{k}$ truck, \$/mile

$\boldsymbol{D_{i,j}}$: Distance between site $\boldsymbol{i}$ and site $\boldsymbol{j}$

$\boldsymbol{Demand_{i,j}}$: Demand between site $\boldsymbol{i}$ and site $\boldsymbol{j}$

$\boldsymbol{PC^{k}}$**:** Price of a brand new type $\boldsymbol{k}$ truck

$\boldsymbol{SI_{w,t,r}^{k}}$: Revenue of a type $\boldsymbol{k}$ truck that purchased at time $\boldsymbol{w}$ and sold at time $\boldsymbol{t}$ in scenario $\boldsymbol{r}$

$\boldsymbol{HC_{w,t,r}^{k}}$: Holding cost of a type $\boldsymbol{k}$ truck that purchased at time $\boldsymbol{w}$ and held at time $\boldsymbol{t}$ in scenario $\boldsymbol{r}$

$\boldsymbol{P_{w,t,r}^{k}}$: Productivity of type $\boldsymbol{k}$ truck that purchased at time $\boldsymbol{w}$ and operated at time $\boldsymbol{t}$, mile/truck in scenario $\boldsymbol{r}$

$\boldsymbol{Prob_{t,r}}$: Probability for each scenario $\boldsymbol{r}$ occurring at time $\boldsymbol{t}$

As seen in Figure 1, the basic transportation network is mapped with two sets, $\boldsymbol{I}$ and $\boldsymbol{J}$, which represent demand sites in an area. The geographical characters of this area are described by the distance matrix $\boldsymbol{D_{i,j}}$. $\boldsymbol{Demand_{i,j}}$ stands for the transportation demand between site $\boldsymbol{i}$ and site $\boldsymbol{j}$. Since both fully-loaded truck fleet and empty-loaded truck fleets are necessary for a logistics system, two decision variables $\boldsymbol{x_{i,j,t}^{k}}$ and $\boldsymbol{y_{i,j,t}^{k}}$ are introduced to represent them respectively. The price of a new truck is assumed to be constant in this paper, while the revenue from selling a truck ($\boldsymbol{SI_{w,t,r}^{k}}$) must reflect the depreciation in value over time. The holding cost ($\boldsymbol{HC_{w,t,r}^{k}}$) is also assumed to increase with time since longer usage of a truck will result in higher maintenance costs. The model similarly assumes that truck productivity ($\boldsymbol{P_{w,t,r}^{k}}$), decreases with time. Moreover, truck productivity could be influenced by various of factors such as mileage range, and thus it is necessary to take the uncertainty of truck productivity into consideration. To solve this problem, specific assumptions on the statistical distribution of truck productivity and a scenario tree are made in the following case study.

Typical transportation cost and emission cost are also included in this model by determining coefficients ($\boldsymbol{c^f}, \boldsymbol{c^e}, \boldsymbol{C^k}$)based on truck travelling distance. Considering all facts and assumptions above, a significant difference in truck fleet operation strategy is expected considering the tradeoff among holding cost, depreciation and productivity.

Figure 4.Operation Strategy Optimization Model Formulation

Objective Function:

$$min \sum_{i,j,k,t} (c^f \cdot y^k_{i,j,t} + c^e \cdot x^k_{i,j,t}) D_{i,j} + \sum_{i,j,k,t} (y^k_{i,j,t} + x^k_{i,j,t}) D_{i,j} \cdot C^k + \sum_{k,w,r} Prob_{t,r} \cdot N^k_{w,r} \cdot PC^k$$

$$+ \sum_{k,w,t,r} Prob_{t,r} \cdot Y^k_{w,t,r} \cdot HC^k_{w,t,r} - \sum_{k,w,t,r} Prob_{t,r} \cdot S^k_{w,t,r} \cdot SI^k_{w,t,r}$$

s.t.

$Demand_{i,j,t} \le \sum_k x^k_{i,j,t}$	$\forall i,j,t$	(1)
$\sum_i x^k_{i,j,t} = \sum_i y^k_{j,i,t}$	$\forall j,k,t$	(2)
$\sum_{i,j} D_{i,j}(y^k_{i,j,t} + x^k_{i,j,t}) \le \sum_w P^k_{w,t,r} Y^k_{w,t,r}$	$\forall k,t,r$	(3)
$Y^k_{w,t,r} = Y^k_{w,t-1,r} - S^k_{w,t-1,r}$	$\forall k,w,t,r$	(4)
$Y^k_{w,t,r} = N^k_{w,r}, if\ w = t$,	$\forall k,w,t,r$	(5)
$S^k_{w,t,r} \le Y^k_{w,t-1,r}$,	$\forall k,w,t,r$	(6)
$S^k_{w,t,r} \ge 0$,	$\forall k,w,t,r$	(7)
$N^k_{w,r} \ge 0$,	$\forall k,w,t,r$	(8)
$Y^k_{w,t,r} \ge 0$,	$\forall k,w,t,r$	(9)
$x^k_{i,j,t} \ge 0$,	$\forall k,i,j,t$	(10)
$y^k_{i,j,t} \ge 0$,	$\forall k,i,j,t$	(11)
$x^k_{i,j,t} = 0, if\ i = j$,	$\forall k,i,j,t$	(12)
$y^k_{i,j,t} = 0, if\ i = j$,	$\forall k,i,j,t$	(13)

$$S_{w,t,r}^{k} = 0, if\ w > t\ , \qquad \forall k, w, t, r \tag{14}$$

$$Y_{w,t,r}^{k} = 0, if\ w > t\ , \qquad \forall k, w, t, r \tag{15}$$

$$N_{w,r}^{k} = 0, if\ w > t\ , \qquad \forall k, w, t, r \tag{16}$$

$$N_{t,s}^{k} = N_{t,s'}^{k} \qquad \forall (s, s') \in R_t,\ \ \forall k, t \tag{17}$$

$$Y_{w,t,s}^{k} = Y_{w,t,s'}^{k} \qquad \forall (s, s') \in R_t,\ \ \forall k, t \tag{18}$$

$$S_{w,t,s}^{k} = S_{w,t,s'}^{k} \qquad \forall (s, s') \in R_t,\ \ \forall k, t \tag{19}$$

The objective function represents the agent minimizing total cost of network, which includes transportation cost of the truck fleet, emission cost of the truck fleet, purchasing cost of new trucks and holding cost for the truck inventory. Note that this model allows used trucks to be sold when necessary by considering the tradeoffs among holding cost, difference in purchasing price and selling revenue and productivity. Therefore, a selling revenue should be subtracted from total cost mentioned above. In general, all constraints should be satisfied under every scenario. Specifically, constraint (1) represents transportation demand between site ***i*** and ***j*** should be covered with full load trucks. Constraint (2) stands for the flow conservation constraint for each node ***j*** in this network; Constraint (3) states that total demand, which is measured as *truck·mile*, should be satisfied with current truck inventory for all time period ***t*** and all scenarios ***r***; constraint (4) represents the state transition process between truck inventory and sale along time ***t***; constraint (5) defines the relationship between truck inventory and purchased trucks, which specifically is when $\boldsymbol{w} = \boldsymbol{t}$ a certain number of trucks ($\boldsymbol{N_{w,r}^{k}}$) is added into inventory; constraint (6) ensures one cannot sell more inventory than last time period; constraint (7) (8) (9) (10) and (11) state the non-negativity of each decision variable; constraints (12) and (13) explains there is no transportation flow within same site; constraint (14) (15) and (16) guarantee that vehicle purchasing time is not a future date. Constraint (17) (18) and (19) are nonanticipativity constraints representing purchasing number, inventory and selling number respectively, where arbitrary scenarios $\boldsymbol{s}$ and $\boldsymbol{s'}$ share the same characters. R_t stands for such scenario bundle sets.

CHAPTER 3

BASE CASE STUDY

Model Formulation and Parameters

In case study one, specific data based on model assumptions are generated to implement the model. The distance matrix is obtained from a real geographic map among five cites in New York state: Ithaca, Elmira, Binghamton, Rochester and Syracuse. From this map, the distance matrix $D_{i,j}$ is derived (Table 1). Note that distance is zero at the diagonal.

Figure 5. New York State Geographical Map

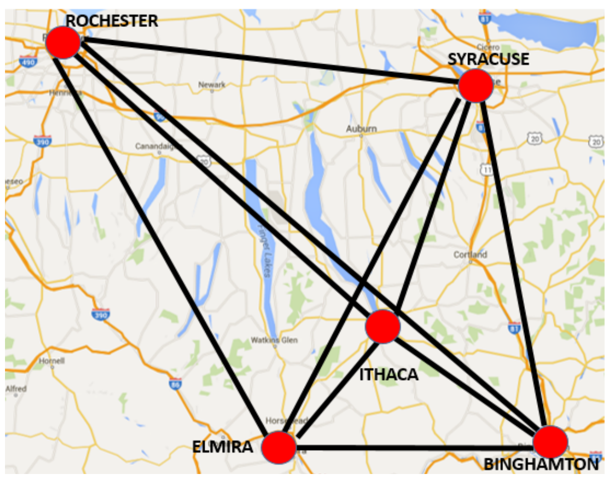


Table 1. Distance Matrix

	Ithaca	Elmira	Binghamton	Syracuse	Rochester
Ithaca	0	33	50	56	90
Elmira	33	0	56	89	105
Binghamton	50	56	0	73	160
Syracuse	56	89	73	0	88
Rochester	90	105	160	88	0

To deal with uncertainty in truck productivity, a scenario bundle of five scenarios is generated and the occurring probability is known in given time horizon. Since the decision process is nonanticipative, which means the decision made at any time period does not depend on future information, this stochastic process of productivity states transition can be described as scenario tree graph below (Figure 6), with S1, S2, S3, S4 and S5 represent each scenario. The probability of each scenario is calculated as conditional probability, based on the probabilities that are randomly generated from uniform distribution U~ [0, 1].

Table 2. Corresponding Probability Matrix for Each Time Period

Scenario / Time	S1	S2	S3	S4	S5
1	0.6	0.6	0.6	0.4	0.4
2	0.6	0.6	0.6	0.4	0.4
3	0.6	0.6	0.6	0.4	0.4
4	0.3	0.3	0.3	0.14	0.26
5	0.3	0.3	0.3	0.14	0.26
6	0.3	0.18	0.12	0.14	0.26
7	0.3	0.18	0.12	0.14	0.26
8	0.3	0.18	0.12	0.14	0.26
9	0.3	0.18	0.12	0.14	0.26
10	0.3	0.18	0.12	0.14	0.26

Figure 6. Scenario Tree Graph for Case Study One

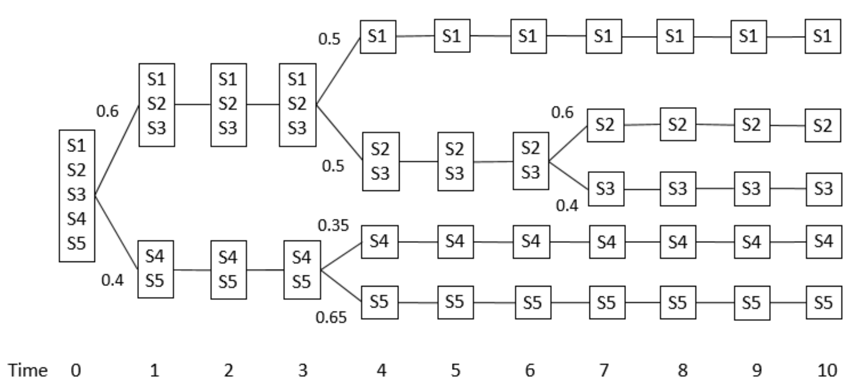


Figure 7. Nonanticipativity Constraints Bundle for Case Study One

$$N_{1,1}^{k} = N_{1,2}^{k} = N_{1,3}^{k} \quad \forall k \tag{11}$$

$$N_{2,1}^{k} = N_{2,2}^{k} = N_{2,3}^{k} \quad \forall k \tag{12}$$

$$N_{3,1}^{k} = N_{3,2}^{k} = N_{3,3}^{k} \quad \forall k \tag{13}$$

$$N_{4,1}^{k} = N_{4,3}^{k}, \forall k \tag{14}$$

$$N_{1,4}^{k} = N_{1,5}^{k} \ \forall k \tag{15}$$

$$N_{2,4}^{k} = N_{2,5}^{k} \ \forall k \tag{16}$$

$$N_{3,4}^{k} = N_{3,5}^{k} \ \forall k \tag{17}$$

$$N_{5,2}^{k} = N_{5,3}^{k} \ \forall k \tag{18}$$

$$Y_{w,1,1}^{k} = Y_{w,1,2}^{k} = Y_{w,1,3}^{k} \ \forall k, w \tag{19}$$

$$Y_{w,2,1}^{k} = Y_{w,2,2}^{k} = Y_{w,2,3}^{k} \ \forall k, w \tag{20}$$

$$Y_{w,3,1}^{k} = Y_{w,3,2}^{k} = Y_{w,3,3}^{k} \ \forall k, w \tag{21}$$

$$Y_{w,4,1}^{k} = Y_{w,4,3}^{k} \ \forall k, w \tag{22}$$

$$Y_{w,1,4}^{k} = Y_{w,1,5}^{k} \ \forall k, w \tag{23}$$

$$Y_{w,2,4}^{k} = Y_{w,2,5}^{k} \ \forall k, w \tag{24}$$

$$Y_{w,3,4}^{k} = Y_{w,3,5}^{k} \ \forall k, w \tag{25}$$

$$Y_{w,5,2}^{k} = Y_{w,5,3}^{k} \ \forall k, w \tag{26}$$

$$S_{w,1,1}^{k} = S_{w,1,2}^{k} = S_{w,1,3}^{k} \ \forall k, w \tag{27}$$

$$S_{w,2,1}^{k} = S_{w,2,2}^{k} = S_{w,2,3}^{k} \ \forall k, w \tag{28}$$

$$S_{w,3,1}^{k} = S_{w,3,2}^{k} = S_{w,3,3}^{k} \ \forall k, w \tag{29}$$

$$S_{w,4,1}^{k} = S_{w,4,3}^{k} \ \forall k, w \tag{30}$$

$$S_{w,1,4}^{k} = S_{w,1,5}^{k} \ \forall k, w \tag{31}$$

$$S_{w,2,4}^{k} = S_{w,2,5}^{k} \ \forall k, w \tag{32}$$

$$S_{w,3,4}^{k} = S_{w,3,5}^{k} \ \forall k, w \tag{33}$$

$$S_{w,5,2}^{k} = S_{w,5,2}^{k} \ \forall k, w \tag{34}$$

This case assumes productivity at each time period is log-normally distributed since productivity is by nature positive. Suppose a positive random variable $\boldsymbol{X}$ is log-normally distributed with mean μ and standard deviation σ, then the logarithm of $\boldsymbol{X}$ is normally distributed. Therefore,

$$N(lnx;\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} exp\,[-\frac{(lnx-\mu)^2}{2\sigma^2}]$$

Then the probability density function of log-normal distribution is:

$$y(x;\mu,\sigma) = \frac{1}{\sigma x\sqrt{2\pi}} \exp\left[-\frac{(lnx-\mu)^2}{2\sigma^2}\right], x > 0$$

And the Cumulative Distribution Function is:

$$Y(x;\mu,\sigma) = \phi(\frac{lnx-\mu}{\sigma})$$

According to Highway Statistics 2013 from Federal Highway Administration, the average Vehicle Miles Traveled (VMT) for a diesel class 8 truck is 68,155 mile/year (*11*). Within each scenario, this model assumes productivity to decrease and uncertainty to increase with time. To achieve this, sample data from log-normal distribution with lower mean and higher standard deviation is generated by *Monte Carlo simulation*. Note that productivity is in ascending order from S1 to S5. It is also assumed that productivity of an electric truck is lower than that of diesel truck since it is still at stage of development. Besides, this study assumes there is sufficient information about diesel trucks so the productivity of diesel trucks is certain.

Figure 8. Productivity of Diesel Trucks

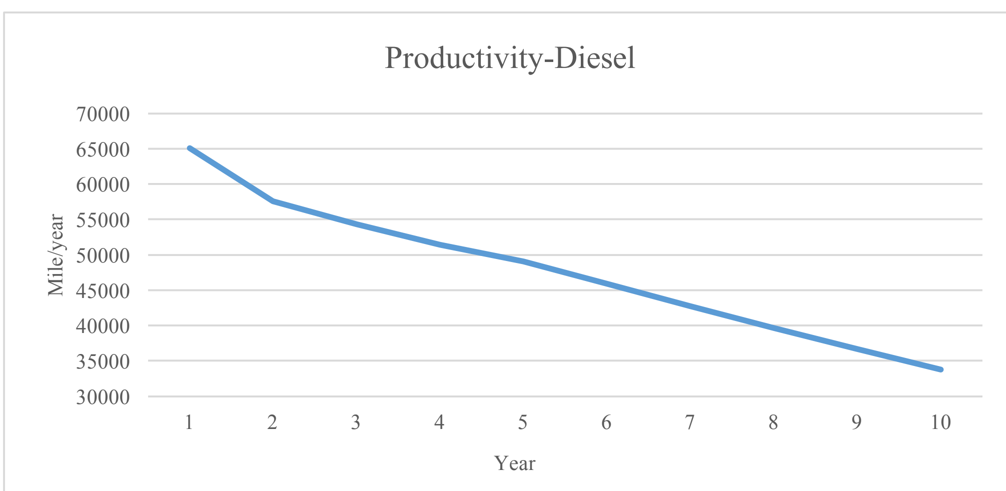
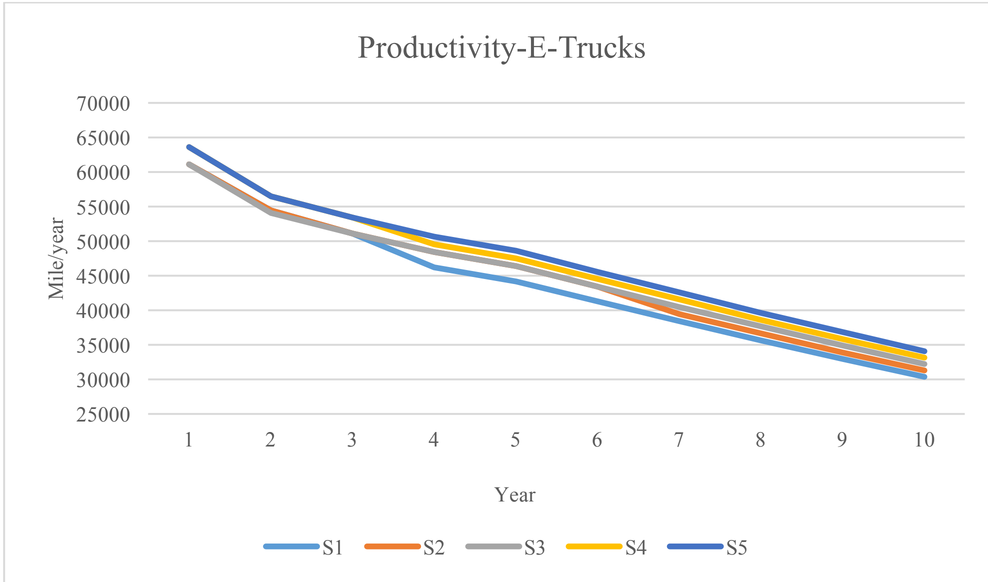


Figure 9. Productivity of Electric Trucks



Also under each scenario, input productivity $P^k_{w,t,r}$ has been shifted from the first time period to purchasing time $\boldsymbol{w}$ according to the gap between $\boldsymbol{w}$ and current time period $\boldsymbol{t}$. For example, $P^k_{3,5,r}$ equals to $P^k_{1,3,r}$. Namely at time 5, the productivity of trucks that purchased at time 3 is the same as at time 3, the productivity of trucks that purchased at time 1.

In this case, random sample data is generated from a uniform distribution U~ [20,120]. This input can be modified to match real demand data and solve for real problems. To simplify, demand data is directly in the unit of trucks, which actually could be decomposed to specific business goods demand. Further, this paper assumes a truck in the transportation network is either fully-loaded or empty to avoid possibility of consolidating shipments.

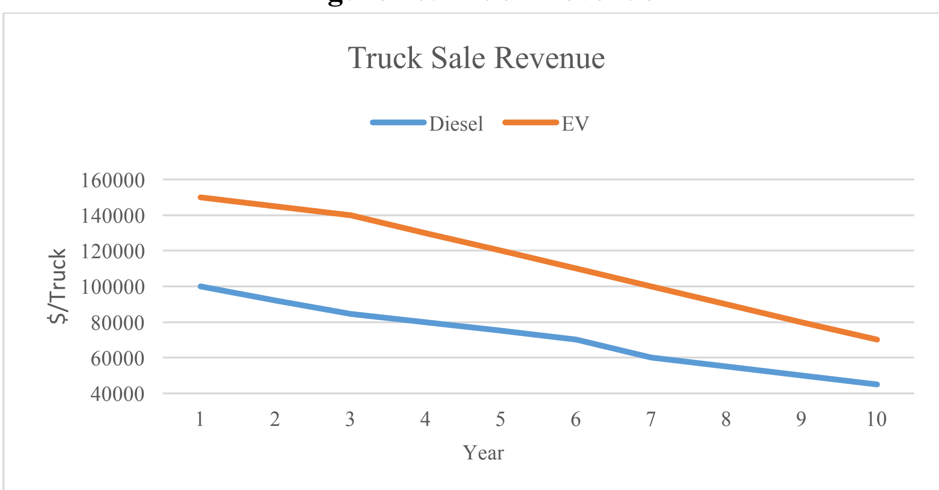
Initial purchasing price, is assumed to be constant for each scenario and time period. This ignores the Net Present Value (NPV) issue in capital budgeting since it is not the focus in this paper. According to a commercial truck trading website, the average price of a new class 8 sleeper truck is around $130,000. As for electric trucks, they are still at growing stage on market. Brian A. Davis *et al.* (2012) took E-star Newton, a pick-up size E-truck as example to discuss the E-truck's competitiveness (*13*). In their paper, they mentioned the purchase price for a brand new E-star Newton electric truck is $149,064. To make a comparison with regular class 8 truck, this thesis assumes the purchase price of a class 8 similar E-truck is $200,000 considering class 8 truck is more expensive than a regular pick-up truck.

Table 3. Truck Price Assumption

Diesel Truck Price	$130,000
Electric Vehicle Price	$200,000

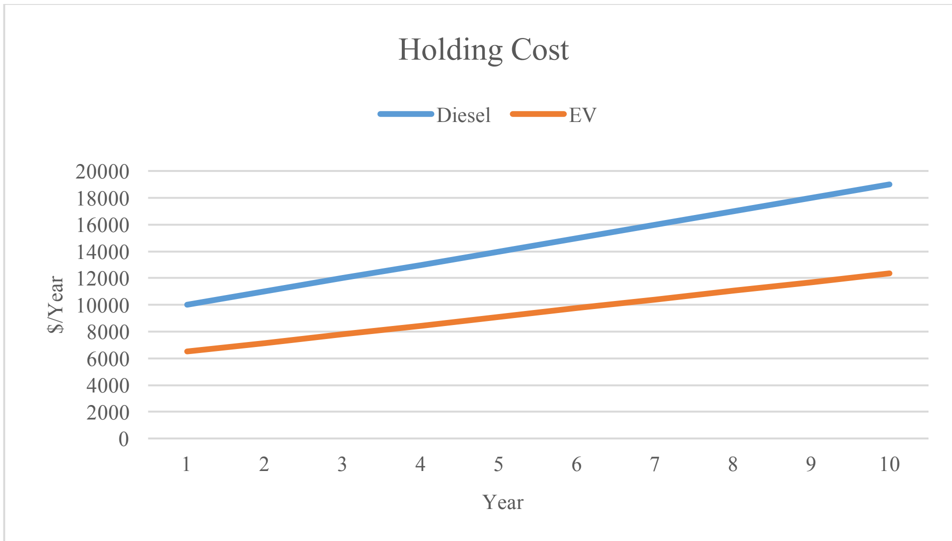
David V. Spitzley *et al.* (2005) discussed life cycle optimization of ownership costs. In their paper, a truck value depreciation profile figure was introduced (*14*), which was taken as reference for the assumption of truck value depreciation in this paper. Furthermore, the depreciation situation is assumed to be identical for each scenario.

Figure 10. Truck Revenue



Similar assumptions are made for holding/ownership cost. However, these costs increase over time. M. Werber *et al.* (2013) delivered a report comparing life-span cost of electric and regular-powered vehicles (*15*). They mentioned that total maintenance cost of electric trucks is 35% lower than that of gasoline vehicles due to more efficient engine and transmission system. Based on their report, this paper assumes holding cost for EV is predicted to be 40% lower than that of diesel truck.

Figure 11. Holding Cost



Davis, Stacy Cagle *et al.* (2016) delivered a market report about vehicle technology in 2015 (*16*). In chapter three, they presented the fuel efficiency of class 8 truck. The miles per gallon ranges from 8 miles to 9.5 miles. In 2011, *National Cooperative Freight Research Program* conducted a project aimed at understanding new dedicated revenue mechanisms for freight transportation investment (*17*). In the following report they claimed the diesel tax per gallon is 24.4 cents/gal. So the parameter assumption for emission cost in this paper is 24.4/8 = 3.05 cents/mile.

The rest parameters including unit transportation cost and emission cost are found in Table 4.

Table 4. Transportation and Emission Costs

Transportation Cost (Full-loaded)	$10/mile
Transportation Cost (Empty)	$7/mile
Emission Cost (Diesel Truck)	$0.0305/mile
Emission Cost (Empty)	$0/mile

Result Interpretation

Code based on commercial optimization software AMPL was developed to solve this multi-stage stochastic programming model. Results are shown in Tables 5 and 6.

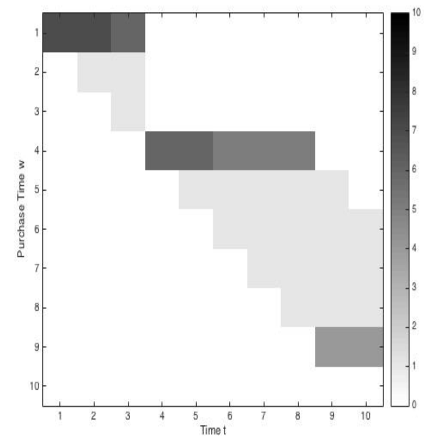
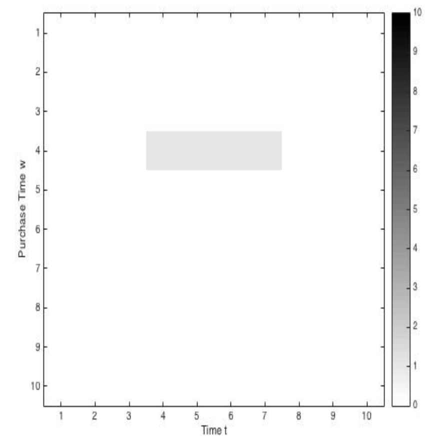
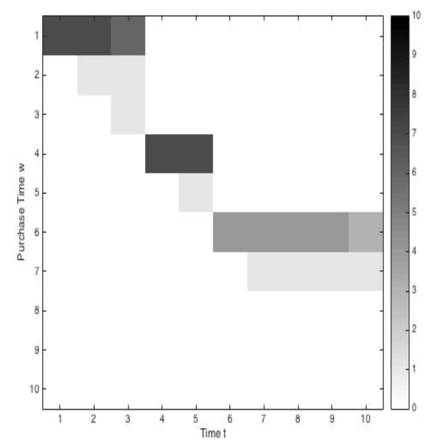
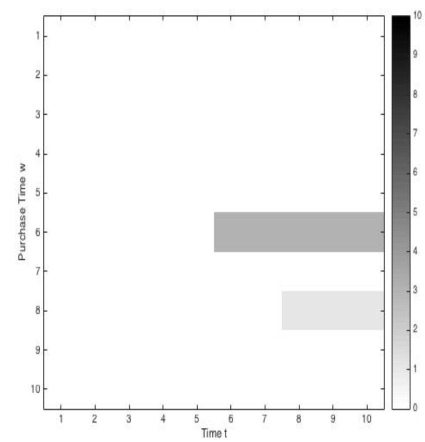
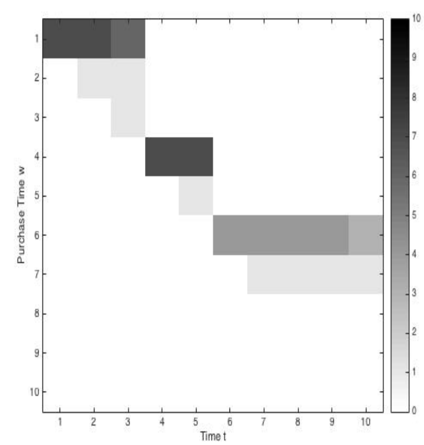
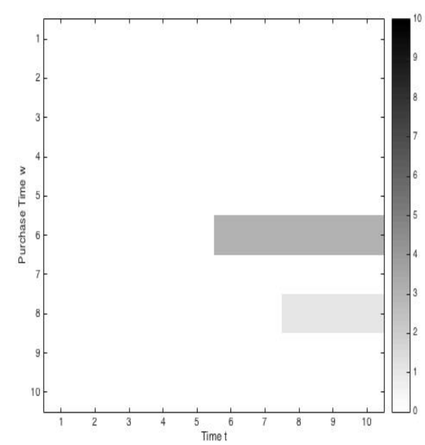
Table 5. Diesel Truck Purchase Plan

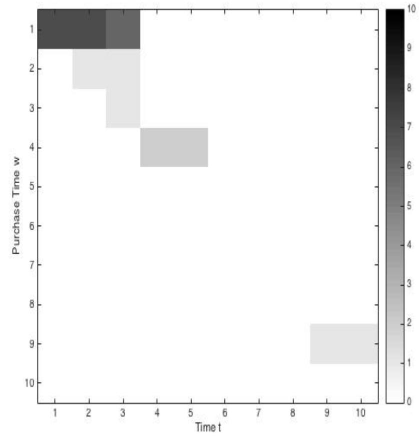
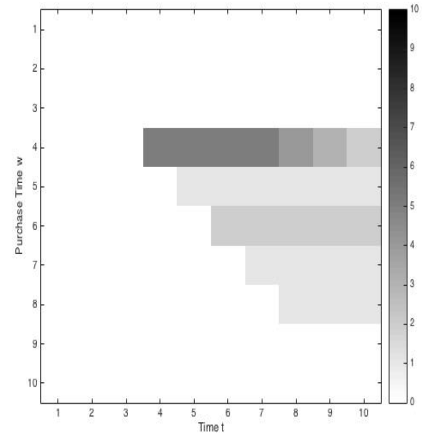
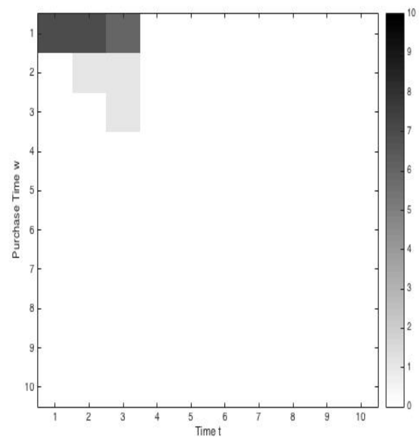
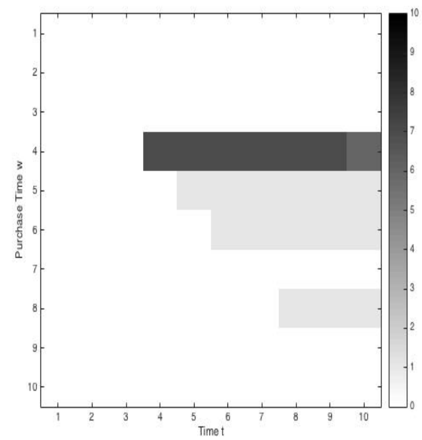
Time \ Scenario	S1	S2	S3	S4	S5
1	7	7	7	7	7
2	1	1	1	1	1
3	1	1	1	1	1
4	6	7	7	2	0
5	1	1	1	0	0
6	1	4	4	0	0
7	1	1	1	0	0
8	1	0	0	0	0
9	4	0	0	1	0
10	0	0	0	0	0

Table 6. Electric Vehicle Purchase Plan

Time \ Scenario	S1	S2	S3	S4	S5
1	0	0	0	0	0
2	0	0	0	0	0
3	0	0	0	0	0
4	1	0	0	5	7
5	0	0	0	1	1
6	0	3	3	2	1
7	0	0	0	1	0
8	0	1	1	1	1
9	0	0	0	0	0
10	0	0	0	0	0

Figure 12. Diesel Truck and E-Truck Inventory

Scenario	Diesel Truck Sale	Electric Truck Sale
S1		
S2		
S3		

S4		
S5		

The result in Table 5 and Table 6 show total diesel truck purchase amount of 88, while that of E-truck is only 29. Figure 12 presents the inventory of two types of trucks over time horizon. There is a clear preference for diesel trucks under all previous assumptions and input data, especially in S1, S2 and S3. In S4 and S5 company tends to choose E-trucks, since E-trucks are more productive in these two scenarios. This model, however, does not consider potential future policies to encourage the use of E-trucks.

CHAPTER 4

POLICY RESEARCH

Kristy Hartman (2015) delivered a report about state efforts promoting new energy vehicles (*18*). According to The U.S. Energy Information Administration, approximately 93 percent of transportation fuel comes from petroleum. With the increasing trend in oil consumption and its significantly negative effect on environment, many states are trying to encourage the usage of alternative energy such as electricity, natural gas, bio-energy, etc. Currently, there are various policies concerning new energy incentives. As a result, several case studies were analyzed using possible alternative energy policies. All case study is based on the same assumptions as case study one.

Case Study Two: Rebate Funding

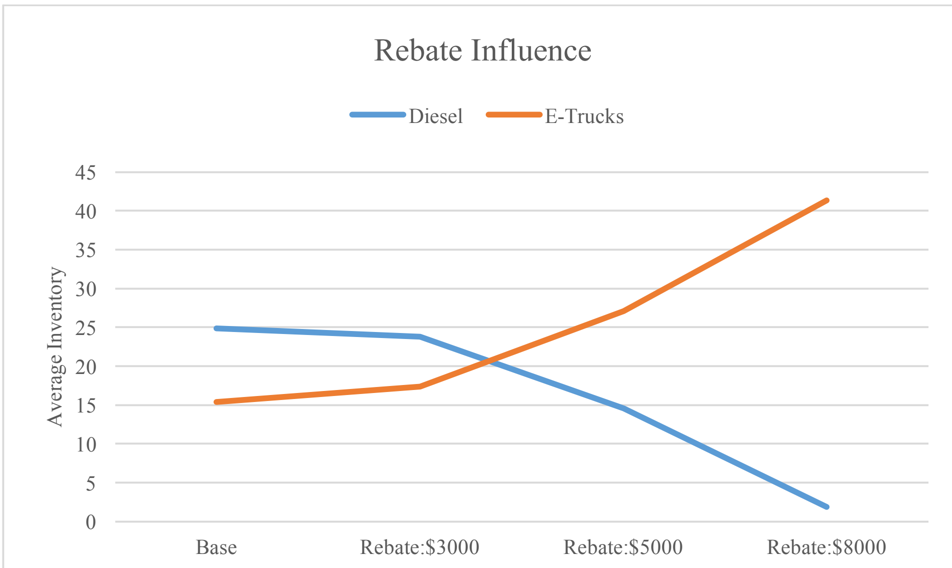
CALSTART report (2012) also did a questionnaire to help them better understand the market situation of E-trucks (*19*). There are several questions about what would spur customers to import E-trucks. According to their results, 46% of the sample consider it is critically important to receive incentive funding for E-trucks purchase, while 44.2% of them highly prefer reduced vehicle cost of E-trucks. In line with public opinion, solid policy had already been lunched to encourage company, government and non-profit organization to purchase electric trucks. In August 2013, Governor Cuomo announced a $19 million New York Truck Voucher Incentive Program (NYT-VIP) to support new energy vehicles. This program guarantees an up to $60,000 rebate for electric vehicles, compressed natural gas vehicles and hybrid vehicles (*20*).

This case study considers rebate as a direct reduction on initial purchase price. Table 7 shows the overall change in average inventory of two types of vehicles as well as the corresponding cost change after conducting this policy for government.

Table 7. Rebate Influence on Average Inventory

	Base	Rebate:$3000	Rebate:$5000	Rebate:$8000
Diesel	24.9	23.8	14.6	1.9
E-Trucks	15.4	17.4	27.1	41.3
Total Cost Change	N/A	-$17,835	-$17,076	-$92,968
Cost Percentage Change	N/A	-0.0047%	-0.0045%	-0.0245%
Government Cost	N/A	$21,000	$155,000	$696,000

Figure 13. Rebate Influence on Inventory



As shown in the Table 7 and Figure 13, overall, the rebate has a significantly positive impact on encouragement of E-truck utilization. With a rebate funding of $8,000, company will almost quit purchasing diesel trucks and turn to E-trucks. Rebate funding will decrease the total cost of logistics company. While from $3,000 rebate to $5,000 rebate, the cost saving effect is about the same, there is a relatively more significant cost saving increase under $8,000 rebate scenario. Government cost to conduct this policy is directly related to the change in electric trucks purchase. This can be a reference when policy budget is limited.

Case Study Three: Carbon Tax

Another potentially functional policy is carbon tax. Metcalf *et al.* (2009) discussed the design of a carbon tax (*21*). In their research, they proved a well-designed carbon tax can deal with about 80% of American emissions. Specifically for transportation, carbon tax essentially equals a fuel tax. In this case, a stepwise carbon tax study is conducted by adding carbon tax to the emission cost in the original term.

Table 8. Carbon Tax Influence on Average Inventory

	Base	$0.0505/mile	$0.0705/mile	$0.0905/mile
Diesel	24.9	17.4	8	5.1
E-Trucks	15.4	23.5	34.2	37.6
Total Cost Change	N/A	$91,095	$148,806	$185,084
Cost Percentage Change	N/A	0.0240%	0.0392%	0.0488%
Government Income	$51,643	$59,752	$38,352	$31,385

Figure 14. Carbon Tax Influence

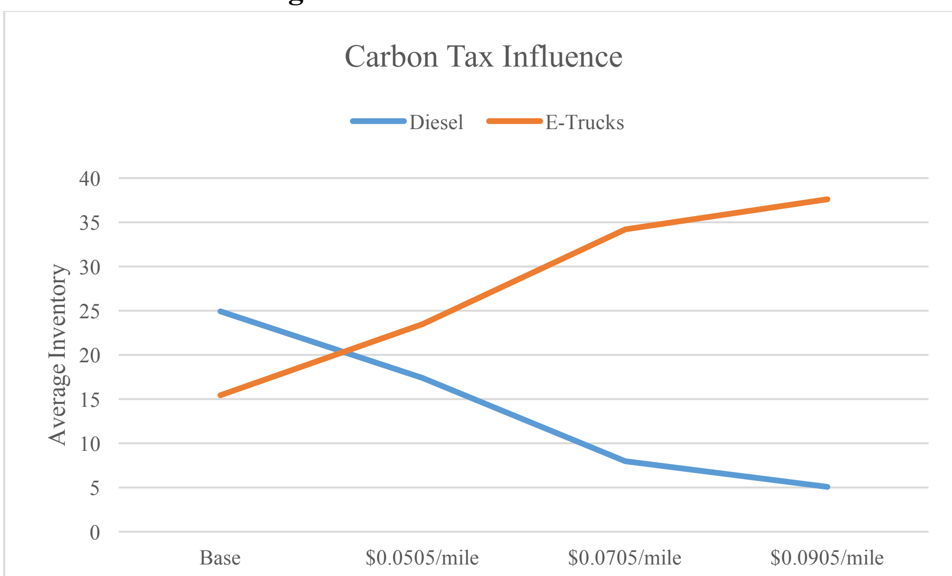


Table 8 and Figure 14 clearly show how the decision changes with an increasing carbon tax. As the figure indicates, charging additional carbon tax will certainly encourage companies to choose E-truck and therefore reduce vehicle emissions. Under the assumptions of this case, when the carbon tax increases to $ 0.0905/mile(three times of the current tax), the average inventory of electric trucks will become 37.6, which is a 144.2% increase. Government gains income from carbon tax policy, which is calculated by the emission cost term in objective function. However, higher tax charge would result lower diesel truck inventory, which will possibly decrease the total tax income. For example, in this case, the total tax income is highest when tax is \$0.0505/mile. There is a potential tradeoff between unit tax charge and total tax income and it can be calculated by optimizing total tax income if necessary.

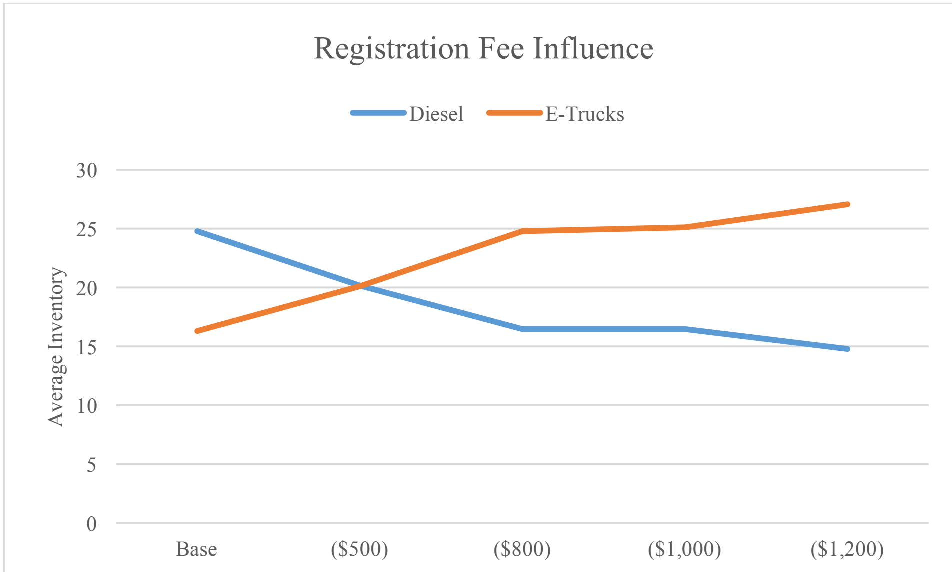
Case Study Four: Registration Fee

In the research of revenue mechanism for freight transportation system conducted by National Cooperative Freight Research Program (2012), an annual or periodic registration fee for class 4-8 trucks is introduced (*22*). The current registration fee system consists of two parts: a federal fee and a state fee. The report also presented some data showing registration fee system has been well developed: \$ 4,953,849,811 net revenue was generated in 2008. For a class 7-8 truck, the annual registration fee is \$1,231. Considering it as part of holding cost, this case further analyzes the potential impact on choice of trucks if registration fee of E-truck is partly exempted, while that of diesel truck remains the same.

Table 9. Registration Fee Reduction Influence on Average Inventory

	Base	-\$500	-\$800	-\$1000	-\$1200
Diesel	24.9	20.2	16.5	16.5	14.8
E-Trucks	15.4	20.1	24.8	25.1	27.1
Total Cost Change	N/A	-\$20,378	-\$29,214	-\$44,051	-56,533
Cost Percentage Change	N/A	-0.0054%	-0.0077%	-0.0116%	-0.0149%
Government Cost	N/A	\$10,050	\$19,840	\$25,100	\$32,520

Figure 15. Registration Fee Influence



This case assumes annual registration fee is a part of annual holding cost and subtract certain amount of cost from E-truck holding cost, which specifically are \$500, \$800, \$1,000, \$1,200 respectively. Table 9 shows the cost to conduct this policy is relatively lower than that of rebate funding policy. As we can see in the Figure 15, company does hold more E-trucks after exemption of registration fee. Under policy of \$800 registration fee exemption, the average inventory of E-trucks will increase 52.1%. However, when the policy offers higher registration fee exemption, the average inventory of E-trucks does not increase much accordingly. This study considers the influence registration fee exemption policy is less significant than the other two policies discussed in case two and case three, under the assumptions, input data and the \$1,200 registration fee limit.

CHAPTER 5

CONCLUSION

This study presents a scenario based multi-stage stochastic programming model to assist logistics company making truck fleet operation decisions. Given a finite time horizon and related input data, operation strategy concerning vehicle type is decided under different scenarios. Nonanticipativity constraints are included to deal with uncertainty. This paper further conducts several case studies to evaluate current policy aimed at supporting the adoption of electric trucks. Judging from the change in inventory of diesel truck and electric truck, the model predicts the rebate funding policy and carbon tax policy to be the more efficient to encourage use of electric trucks. Furthermore, if extra finance income is necessary, carbon tax policy will function better. To simplify, most of the data of this paper is generated by Monte Carlo Simulation. If modified with real industry data, I believe this model could be applied into practice and provide helpful suggestions on how the new energy incentive policy could best achieve its goal. Further research could include exploration of the feasibility of every assumption in this model such as the statistical distribution of productivity, or could include a study on empirical functions of productivity based on historical data. This model can also serve as a reference for the draft of new policy.

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