THE COMPETITIVENESS OF COMMERCIAL ELECTRIC VEHICLES IN THE LTL DELIVERY INDUSTRY: A MODEL AND APPLICATION

Brian A. Davis
Portland State University
Department of Civil and Environmental Engineering
P.O. Box 751
Portland, Oregon 97207-0751
Phone: 503-929-4551
Fax: 503-725-5950
Email: bdavis@pdx.edu

Miguel A. Figliozzi
Portland State University
Department of Civil and Environmental Engineering
P.O. Box 751
Portland, Oregon 97207-0751
Phone: 503-725-4282
Fax: 503-725-5950
Email: figliozzi@pdx.edu

Submitted for presentation to the 91st Annual Meeting of the Transportation Research Board
January, 2012

Submitted for Publication to Transportation Research Part E: Transport and Logistics

Submitted July 2011

Abstract

We have developed a detailed model of the logistics performance, energy use, and costs of electric vehicles and comparable diesel internal-combustion engine vehicles. This effort is a novel study of commercial electric vehicles because the implications of routing constraints, route parameters, and electric truck characteristics are analyzed integrating three models: (a) a vehicle ownership cost minimization model, (b) a model to calculate the power consumption and maximum potential range of an electric or conventional truck as a function of average velocity and weight, and (c) a continuous approximation model to estimate fleet size, distance traveled, and ensure that practical routing constraints are satisfied. The model is applied to the study the competitiveness of three vehicles of similar weight and size in the USA market: a widely available conventional diesel truck and two electric trucks. Scenarios and breakeven points are calculated and analyzed for a large number of parameter combinations. The results provide new insights regarding the truck characteristics and logistical constraints that determine whether a conventional or electrical truck is more cost effective.

Keywords: urban deliveries, commercial electric vehicles, LTL deliveries, vehicle replacement

1. Introduction

Political and practical considerations have produced an environment that is increasingly conducive to a growing presence of electric vehicles. The 2009 economic stimulus package in the United States contained $2.4 billion in the form of DOE grants to "accelerate the manufacturing and deployment of the next generation of US batteries and electric vehicles" (USDOE 2009). Many of the recipients of these grants have recently introduced new products. Empirical evidence suggests that the deployment of a new generation of electric vehicles (EVs) is well underway, with companies such as Frito Lay, Fed Ex, and others making recent deployments of this technology. Other countries, e.g. China and Germany, have undergone a similar push to electrify portions of their vehicle fleets in recent years. While this paper focuses on US fleets and uses some numbers that are unique to this country (e.g., fuel prices), the methodology presented here could easily be applied to any country or region.

Electric delivery trucks are a relatively new innovation, part of a current generation of electric vehicles, made possible by improving battery technology capable of moving delivery trucks with gross vehicle weight ratings in the 10,000 lb – 20,000 lb range (Federal Highway Administration Class 3,4 and 5 in the USA) as much as 80-100 miles on a charge. This research aims to quantify the lifetime costs of serving particular routes with the new generation of electric delivery trucks. To this end, equations linking vehicle performance to power consumption, route characteristics, fleet sizes, and travel distances are developed. **Table 1** shows the specifications of the three types of truck considered in this research

Table 1: Specifications of three trucks considered in the model.

	Navistar E-Star	Smith Newton	Isuzu N-Series
Price	$149,900	$150,000	$60,000
Battery Size	80 kWhr	80 kWhr	~360 kWhr*
Range	100 mi	100 mi	~350 mi
GVW	12,100 lbs	16,535 lbs	12,000 lbs
Tare	8,100	9,143	5,672
Payload	4,000	7,392	6,328

* Battery power and range equivalents for the conventional truck were calculated according to the methods and figures suggested by *High Voltage* (Economist 2010)

The rest of this paper is organized into seven sections. Section 2: a literature review is presented to summarize existing work exploring electric vehicles, battery technology, and some of the logistics concepts covered in this paper; Section 3: the methodology section describes the modeling framework employed in the research; Section 4: data sources are identified; Section 5: a description and analysis of 128 scenarios are presented; Section 6: a sensitivity analysis is performed using parameter elasticities; Section 7: a breakeven analysis that investigates where the EV's become competitive is performed; Section 8: conclusions are presented.

2. Literature Review

While the body of research pertaining specifically to electric delivery trucks is fairly young, previous research exists on the various components upon which this research is built. One of the most ambitious projects examining the potential for electric trucks to serve urban delivery routes is the Electric Vehicle City Distribution (ECLIDIS), a project spanning distribution centers in six European cities from 1998 to 2002. In a report commissioned by the European Union (Vermie 2002), the ECLIDIS program is deemed an overall success, although the purchase cost of electric vehicles is identified as a substantial barrier to widespread implementation.

A more critical review of this program is presented by Jeeninga et al.(2002), who survey carriers and drivers through the lifespan of this project and report that the vehicles performed below expectations in terms of range, speed and acceleration, and reliability. Van Rooijen et al. (2010) reach similar conclusions, and cite the need for better logistical support for electric vehicles.

Given the importance of the cost and quality of the batteries that power electric vehicles, much work has been done studying the properties and life spans of the several generations of batteries that have powered electric vehicles. Knipe et al. (2005) reviewed the performance of Nickel Metal Hydride batteries in Toyota RAV4 EV's after reaching 100,000 miles, and found that they retained about 85% of their initial power storage capacity, although the decrease in range outpaced that of capacity. A more recent study (Smith EV 2010) of the lithium ion batteries that power the Smith Newton electric trucks finds that they will retain 80% of their initial capacity after 3,000 cycles of fully charging and discharging.

In terms of charging infrastructure, Botsford & Szczepanek (2009) discuss the various trade-offs between fast charging and slow charging, and discuss the concept of "range anxiety" and its effects on utilized range, and how these concepts are affected by the charging mechanisms. This emphasizes the need for better connection flow for charging electric vehicles. Along these lines, Conrad et al. (2011) recently introduced the Electric Vehicle Routing Problem, a special case of the VRP that takes into account the limited range of EV's.

In the US, a recent report from the Electrification Coalition (2010) provides a wealth of information regarding the cost and operation of electric vehicles as well as internal combustion engine (ICE), hybrid, and plug-in hybrid vehicles. Using this information, Feng & Figliozzi (2011) present a vehicle replacement model that allows for the purchase of either a conventional truck or electric truck at each decision point. Under the present conditions, they show that electric trucks are only competitive if utilization is high and if EV prices fall 15 to 30%.

As trucks are introduced to the market place, several large companies have begun testing them in the field. Federal Express announced the introduction of Navistar's E-Star trucks to its fleet in

March, 2010 (FedEx 2010). In September, Frito Lay announced the beginning of a deployment of 176 Smith Newton trucks (Motavalli 2010). Some fairly positive press coverage in the wake of these announcements by both companies makes it likely that competitors will follow suit. Despite the growing interest in EV technology and the fact that many large companies have recently put electric trucks into service, there is no study of the relationships between the logistical parameters and costs of operating these vehicles. This research aims to cover this gap. The authors believe that the integration of a power consumption and logistics model to electric delivery trucks is a new contribution to the literature.

3. Methodology

I. Cost Minimization Model

In order to calculate the costs of serving a route with a certain truck, it is useful to first formulate a model for minimizing the costs given the routing constraints. Identifying the individual cost components provides a roadmap for calculating the total costs for each truck.

Indices:

I = trucks considered, indexed by i; $i \in \{1,2,3\}$

K = planning horizon, indexed by k; $k \in \{1,2,\dots,K\}$

Decision variable:

m^i = number of trucks of type *i* to service all the daily customer demands

Costs:

c_{tot}^i= total cost for truck *i*

c_p^i= purchase cost for truck *i*

c_e^i = energy cost for truck *i*

c_m^i= maintenance cost per mile for truck *i*

c_b^i= battery replacement cost for truck *i*

c_t^i = tax incentive for the purchase of truck *i*

Inflationary factors:

f_d = discount factor

f_e = rate of inflation in electricity or fuel costs

Other parameters:

f(m) = electricity or fuel consumed per day by all vehicles

d_s = days of service per year

L(m) = daily distance travelled to serve route by all vehicles

E_{tot}^i = total fleet energy required, for truck type *i* fleet, to serve the daily customers

E_{bc}^{i} = battery capacity (or equivalent tank capacity) for truck type *i*
W_{cd} = total daily customer demand
W_{pay}^{i}= payload capacity for truck type *i*
t_{tot} = total time necessary to travel to customer locations and serve customers
t_{max} = maximum permissible route time

$Minimize$

$$c_{tot}^{i} = c_{p}^{i} m^{i} + \sum_{k=1}^{K} (1+f_d)^{-k} \left[(1+f_e)^{k} c_{e}^{i} f(m^{i}) d_s + c_{m}^{i} L(m^{i}) \right] + c_{b}^{i} m^{i} - c_{t}^{i} \quad (1)$$

$\forall i \in I$

s.t.

$$\frac{E_{tot}^{i}}{m^{i}} \leq E_{bc}^{i} \; \forall i \in I \quad (2)$$

$$\frac{W_{cd}}{m^{i}} \leq W_{pay}^{i} \; \forall i \in I \quad (3)$$

$$\frac{t_{tot}}{m^{i}} \leq t_{max} \quad (4)$$

$$m^{i} \geq 0 \quad (5)$$

$$m^{i} \in Set\ of\ Integers \quad (6)$$

Equation 2 is the energy constraint, stating that the energy consumed by the electric truck must be less than its battery capacity or that the energy consumed by the diesel truck must be less than its tank capacity; equation 3 is the cargo constraint, stating that each truck must carry less than its payload capacity, and; equation 4 is the time constraint, stating that the sum of travel time and time spent serving customers must be less than a maximum allowable route duration. The number of trucks used of course must be a positive integer (equations 5 and 6).

For the conventional truck, fuel consumption was modeled using existing data and research on fuel consumption as a function of velocity and weight. Coyle (2007) shows that the fuel economy of trucks is reduced by approximately 1 mpg for every 8 tons of payload the truck carries. This yielded results that were in-line with real-world data obtained by the authors measuring the actual performance of the Isuzu N-Series trucks.

II. Continuous approximation model

The research presented here attempts to estimate the cost of serving routes with certain properties with the considered trucks by using a continuous approximation of the Vehicle Routing Problem (VRP). Continuous approximation methods use estimations that are based on the spatial (and/or temporal) density of demand rather than on precise information about the location and demand of each customer. As the number of these discrete points (i.e., customers) grows, it can be more closely approximated by a continuous function. This planning-level approximation is useful for deriving insights about the relationships between parameters and capturing key variables affecting cost (Langevin et al. 1996).

A continuous approximation method was first proposed by Beardwood et al. (1959) and has been refined and applied to many different situations over the years by Daganzo (2005) and others. Langevin et al. (1996) provide a comprehensive review of these approximations and their applications. Beardwood's approximation for the TSP tour distance is given by:

$$L(n) = k_1\sqrt{nA} \tag{7}$$

where n is the number of customers and A is the area of the space over which the customers are distributed, and k_1 is a constant. From this, it's easy to see that a VRP which originates at a single depot some distance k_2 from the center of the service area, the tour length can be approximated by:

$$L(n) = k_1\sqrt{nA} + k_2 m \tag{8}$$

where m is the number of trucks or routes necessary to serve the customers, and k_2 is the distance from the depot to the center of the service area (Daganzo 2005). It's important to note that this formulation makes additional assumptions about the structure of the problem. The introduction of the second term implies that the number of trucks needed to serve the route is a known quantity at the outset, which is to say that customer demand is known and constant. Also, the real-world manifestation of this term is actually the distance each truck must travel from the depot to its first customer and from its last customer back to the depot. Since the distance from the depot to the center of the service area is used in this approximation, it becomes more accurate as this distance is increased relative to the size of the service area.

The approximation is further refined by Figliozzi (2008) who proposes the term $(n-m)/n$ to modify the local tour distance:

$$L(n) = k_1\frac{n-m}{n}\sqrt{nA} + k_2 m \tag{9}$$

where k_1 and k_2 are parameters that depend on the route constraints and customer characteristics, and can be readily estimated by linear regression. The first term represents the distance travelled as the vehicles serve customers within the service area, while the second term corresponds to the trip from the depot to the service area. The value of this term approaches zero as the *n* approaches *m*, so its inclusion of this term corrects the overestimation of the local tour distance in such situations. In cases where *n* is large relative to *m,* the first term tends toward the model proposed by Beardwood. Thus, provided the assumptions regarding known customer demands and a fairly high depot distance hold, this model provides a good approximation of tour length.

It follows that each tour can be divided into three segments with known route distances and average weights: (1) the trip from the depot to service area; (2) the trip within the service area, and; (3) the return trip from the service area to the depot. This configuration is illustrated in **Figure 1.**

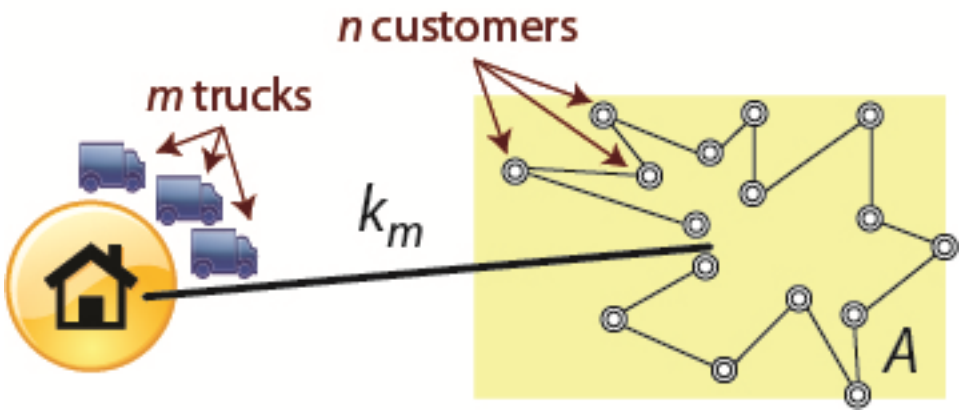

Figure 1: Illustration of the configuration of the vehicle routing problem considered in this research.

For each of the *m* trucks, the first leg of the tour (leg 'a'), the trip from the depot to the service area, has an associated distance D_a given by:

$$D_a = \frac{1}{2}k_2 \tag{10}$$

The truck weight W_a is given by:

$$W_a = W_t + \frac{W_{cd}}{m} \tag{11}$$

where W_t is the tare weight of each truck and W_{cd} is the average demand weight for each of the *n* customers.

The second leg (b), the trip within the service area, has an associated distance and average truck weight given by:

$$D_b = k_1 \frac{n-m}{n} \sqrt{An} \tag{12}$$

$$W_b = W_t + \frac{W_{cd}}{2m} \tag{13}$$

The last leg (c), the return trip from the service area to the depot, has an associated distance and truck weight given by

$$D_c = \frac{1}{2} k_2 \tag{14}$$

$$W_c = W_t \tag{15}$$

It is clear from this formulation that the weight of the truck is the highest on the first (outward from the depot) leg; this value is constrained by the gross vehicular weight of the truck. Subtracting out the tare weight of the truck, the capacity constraint is obtained:

$$\frac{W_{cd}}{m} \leq W_{pay} \tag{16}$$

Another hard constraint that follows is that the total distance travelled must be less than the maximum range of the truck, particularly for the electric trucks which cannot easily refuel en route. This constraint is developed as an energy constraint in the next section.

To the best of the authors' knowledge, this is the first application of a continuous approximation model to electric vehicles. This research assumes that routes are balanced (i.e., n/m customers per route), and assumes capacity constraints but also that there is no time sensitivity in the deliveries, i.e., the customers can be served in any order. However, the impact of time windows could be easily incorporated using the appropriate approximation (Figliozzi 2008).

III. Power consumption model for electric trucks

The costs of serving certain routes are estimated for two electric trucks—a Navistar E-Star and a Smith Newton—and for a conventional Isuzu N-Series truck for which the researchers had existing data on mileage per gallon. The properties of these trucks are shown in **Table 1.** While the weight ratings of the three trucks are fairly similar (indeed, these particular trucks were chosen so this is the case), the price difference between the electric and conventional vehicles immediately begs the question of whether the lower operating costs over the lifetime of the

electric trucks will be sufficient to justify the higher purchase cost. The effects of the smaller range of the electric vehicles are also examined here.

To calculate the energy consumed along each leg, it is useful to note that a truck uses energy in three ways: to navigate grades, to accelerate, and to overcome aerodynamic and rolling resistance.

The energy (in ft-lbs) required to accelerate the truck to a velocity v (in mph) is simply equal to the change in the kinetic and gravitational potential energy of the truck divided by the efficiency of the engine *eff*.

$$E_{acc} = \left(\frac{1}{2}Mv^2 + W\Delta h\right)/eff \tag{17}$$

where M is the mass of the truck in slugs, determined by dividing the weights obtained from equations 11, 13, and 15,), by the gravitational constant g=32 ft/s^2, and Δh is the change in height encountered during this acceleration.

Mannering et al. (2008) present a well-known equation for calculating the power consumption of a vehicle moving at a constant velocity v:

$$P = \frac{\rho C_D A_f v^3}{2} + f_{rl}Wv + GWv \tag{18}$$

where P is the power consumed in ft-lbs/s, ρ is the air density in slugs/ft^3, C_D is the coefficient of drag (unitless), A_f is the frontal area of the vehicle in ft^2, f_{rl} is the coefficient of rolling resistance (unitless), G is the grade of the roadway, and W is the weight of the vehicle in lbs.

The energy (in ft-lbs/s) consumed by a vehicle moving at this velocity for a time t (in seconds) is then given by:

$$E_{res} = \left(\frac{\rho C_D A_f v^3}{2} + f_{rl}Wv + GWv\right) * t/eff \tag{19}$$

If the average speed for leg 'a' of the route is v_a, the average speed for leg 'b' is v_b, and the average speed for leg 'c' is v_c, it is then possible to estimate the total energy consumed by traveling the route by combining equations 17 and 19 with the corresponding components of equation 9. Noting that each truck accelerates once from the depot, once from the service area to the depot, and that all trucks together accelerate n times within the service area, the total energy consumed serving the route is given by:

$$E_{tot} = f(m) = \frac{1}{eff}\left\{\begin{array}{c} \left(\frac{1}{2}M_a v_a^2 + W_a \Delta h_a\right)m + \left(\frac{\rho C_D A_f v_a^3}{2} + f_{rl} W_a v_a + G W_a v_a\right)\frac{k_m m}{2 v_a} \\ \left(\frac{1}{2}M_b v_b^2 + W_b \Delta h_b\right)n + \left(\frac{\rho C_D A_f v_b^3}{2} + f_{rl} W_b v_b + G W_b v_b\right)\left(\frac{k_1 \frac{n-m}{n}\sqrt{An}}{v_b}\right) \\ + \left(\frac{1}{2}M_c v_c^2 + W_c \Delta h_c\right)m + \left(\frac{\rho C_D A_f v_c^3}{2} + f_{rl} W_c v_c + G W_c v_c\right)\frac{k_m m}{2 v_c} \end{array}\right\} \quad (20)$$

From here, it is straightforward to convert this energy into kilowatt hours and multiply by a known cost of electricity (divided by an assumed charging efficiency) to obtain a monetary cost of serving this particular route. For electric vehicles, this also involves assuming some factor for regenerative breaking, as suggested by Sandalow (2009) and Panagiotidis et al. (2000).

4. Data Sources

In addition to the energy costs and the purchase cost for *m* trucks, we also assume a certain maintenance cost for the electric trucks and their conventional counterpart. These values are shown in **Table 2.**

Finally, we must assign a cost to battery deterioration or replacement in the electric vehicle to get a complete picture of the costs. Unfortunately, no real consensus exists in the literature of the lifetime of the batteries used in the electric trucks considered here, although Knipe et. al (2005) have found very good lifetimes from earlier generations of batteries like those used in the Toyota Rav4. Using that result along with projections from Kilcarr (2010), we assume one battery replacement will be necessary over the lifetime of each EV at a cost of $400 per kWhr of capacity. This amounts to an additional one-time cost of $32,000 for each of the two electric trucks considered in this work. New internal research conducted by Smith Electric Vehicles, however, found that the lithium ion batteries used to power their trucks retained 80% of their initial capacity on average after 3,000 cycles (Smith EV 2010) of fully discharging and recharging the battery. If true, the battery would rarely need to be replaced during the planning horizon examined in this work. Given the importance of battery costs to the total cost of operating an electric vehicle, both possibilities are considered in this research.

5. Baseline Case and Extreme Scenarios

A baseline case is considered that includes the lowest and highest values for seven parameters—the number of customers, the service area, the depot-service area distance, the customer service time, the customer demand weight, the cost of diesel fuel, and the cost of electricity—that might be encountered in Portland, OR using values obtained in July 2011. These values, listed in Table 2, lead to 128 (2^7) different scenarios, as each of the possibilities was considered along with all

possible others. The cost per customer of serving each route is determined and a 'winner' is determined by which truck can serve the route for the lowest cost.

A summary of the results of the 128 "extreme" scenarios for the base case is shown in **Figure 2.** Figure 2a shows the scenarios in which the N-Series is the best option, Figure 2b shows the scenarios in which the E-Star is the best option, and Figure 2c shows the scenarios in which the

Table 2: Low and high values for route parameters used to determine the best trucks for the 128 extreme scenarios.

Parameter	Low Value	High Value
Round trip depot-service area distance k_2[1]	20 mi	60 mi
Number of customers n[2]	20	150
Customer service time t_{cs}[3]	6 min	30 min
Demand weight w_{cd}[4]	10 lbs	500 lbs
Service Area a[5]	25 mi^2	100 mi^2
Diesel cost[6]	$1.99/gal	$5.96/gal
Electricity cost[7]	$0.0552/kWhr	$0.1656/kWhr
Air Density ρ[8]	0.002378[1]	
Drag coefficient C_D[8]	0.7	
Frontal area A_f[9]	50 ft^2	
EV Engine Efficiency[10]	0.8	
EV Charging Efficiency[10]	0.8	
Regenerative Braking Potential[10,11]	.2	
Average Speed (Depot to SA)[12]	40 mph	
Average Speed (Within SA)[12]	20 mph	
Maintenance Costs[13]	$0.20/mi for conventional vehicle $0.10/mi for electric vehicle	
Battery Replacement Cost[14]	$32,000	
Time constraint[15]	9 hrs.	
Diesel truck MPG[16]	10	
Discount Factor[17]	6.5%	
Fuel Inflation Rate[17]	2.5%	

1. Low value corresponds to approximate distance between Northeastern industrial area and CBD in Portland; high value corresponds to approximate distance between Wilsonville industrial area and CBD in Portland.
2. Low value intended to simulate a Staples- or Frito Lay-type customer load; high value intended to simulate a FedEx-type customer load.
3. Low value intended to simulate a FedEx-type customer service time; high value intended to simulate a Staples- or Frito Lay-type customer service time.
4. Low value intended to simulate a FedEx-type demand weight; high value intended to simulate a Staples- or Frito Lay-type demand weight.

5. Low value is approximately the size of Portland's CBD; high value is approximately the area within Portland city limits
6. Corresponds to 50% and 150% of current nationwide diesel prices per USDOE [http://www.eia.doe.gov/oog/info/gdu/gasdiesel.asp, retrieved on April 12, 2010]
7. Corresponds to 50% and 150% of current nationwide electricity prices, averaged across sectors USDOE [http://www.eia.doe.gov/electricity/epm/table5_6_b.html, retrieved on April 12, 2010]
8. Mannering et al., 2008
9. Assumes approximately 5 ft wide by 10 ft high frontal projection.
10. Shah 2009
11. Panagiotidis et al. 2000
12. Assumed travel speeds based on typical values for Portland arterials and streets within CBD
13. Motavalli 2010
14. Kilcarr 2010
15. Typical time constraint for logistics problems
16. From data for Isuzu N-Series trucks
17. Feng et al. 2011

Newton is the best option. The blue (bottom) portion of each bar corresponds to the number of scenarios the given truck wins when that particular parameter takes its low value, and the red (top) portion corresponds to the number of scenarios the given truck wins when the parameter takes its high value. The sum of the bottom and top parts of each bar is equal to the total number of the 128 scenarios that the given truck wins; the sum the stacked bars for each of the seven parameters over all three trucks is equal to 128. Thus, Figure 1 shows 106 wins for the N-Series conventional truck and 22 for the electric trucks (15 for the E-star and 7 for the Newton).

As one might expect, the cost of diesel is one of the more important factors in determining the best truck for each scenario; the conventional truck is the best in all 64 scenarios where diesel is high, and only 42 where diesel is low. Almost as important is the depot-to-service area distance. The conventional truck is best in 62 where this distance is low, and 44 where it is high. Since the maintenance and operating costs of the electric trucks are low compared to the diesel trucks, it follows that the electric trucks will perform better as the route distance increases.

Another interesting parameter here is the customer demand weight. At high demand weights, the conventional truck tends to outperform the electric truck, as any factor that requires the purchase of additional trucks (such as heavy demand weights such that the capacity constraint is binding) favors the cheaper conventional vehicles. Comparing the two electric trucks, the higher-capacity Newton wins in all scenarios where the demand weight is high, and the E-Star wins in all scenarios where this is low.

The sensitivity of the various assumptions regarding speed, battery replacement cost, the time constraint, and tax incentives is tested by varying these and producing new results for these 128 scenarios.

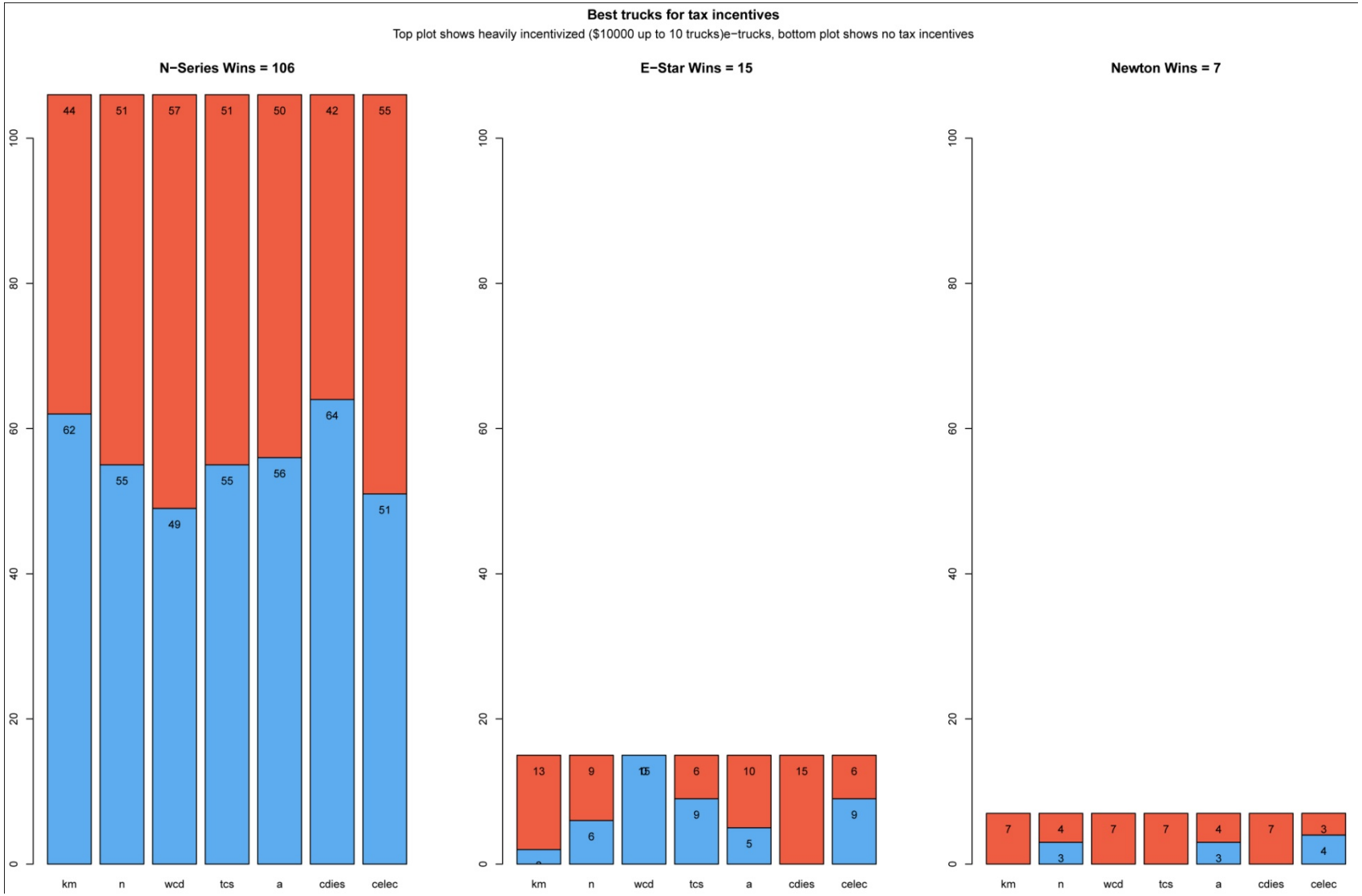

Figure 2: Number of the 128 "extreme" scenarios in which each truck is the least expensive option, assuming one $32,000 battery replacement. Red indicates scenarios in which the parameter takes the higher value, and blue indicates scenarios where it takes the lower value.

Table 3 examines how these results are affected by different assumptions about the battery replacement cost. Since the battery cost is such a large part of the initial purchase cost of the electric truck, perhaps it is not too surprising that the assumptions made about the replacement of the battery have a fairly large effect on the performance of the e-trucks. If, as the study from Smith suggests, no battery replacement is necessary over the lifetime of the vehicle, the electric trucks are then the best option in 15 additional high-diesel scenarios, enough to then be a majority. Conversely, if technology remains at present-day costs, the electric trucks only win out in 8 of the 128 scenarios.

Since any factor that triggers the purchase of additional trucks is beneficial to the conventional trucks, it's useful to look at how different values of the time constraint affect the overall results. The baseline time constraint is assumed to be 9 hours, a fairly typical shift time or depot working time. Relaxing this constraint by one hour results in two additional wins for the electric trucks, and tightening it results in five additional wins for the conventional truck. This value, therefore, is not terribly important to the overall results for most realistic values.

Table 3: Numbers of scenarios in which each truck is the least expensive option given different assumptions regarding battery replacement cost, time constraint, tax incentives, travel speeds, and road grades.

		N-Series Wins	E-Star Wins	Newton Wins
	Base Conditions	106	15	7
Battery	$50,000	120	6	2
Replacement	No Cost	91	22	15
Time	10 hr	104	17	7
Constraint	8 hr	111	13	4
Tax Incentives	Heavily Incentivized[1]	102	18	8
	No Incentive	106	15	7
Speeds	High Speeds[2]	108	14	6
	Low Speeds[3]	118	8	2
Grade	Best Case[4]	102	16	10
	Worst Cast[5]	106	15	7

1. Assumes a $10,000 tax credit per truck up to 10 trucks.
2. Assumes depot-to-service area speed of 50 mph and within-service area speed of 30 mph
3. Assumes depot-to-service area speed of 30 mph and within-service area speed of 10 mph
4. Assumes 3% grade from depot-to-service area and -3% grade returning.
5. Assumes 3% grade from depot-to-service area and -3% grade returning.

As governments attempt to increase the electrification of national vehicle fleets, one common discussion is what can be done to incentivize the purchase of electric trucks. The baseline

scenario assumes the current US tax policy of a $2,500 tax credit for up to three electric vehicles. Even if electric trucks were heavily incentivized by allowing for a $10,000 tax credit for up to 10 trucks, these vehicles would only win in three additional scenarios. Eliminating the tax credit entirely produces the same results as the baseline scenario. Any realistic incentive, then, is likely to be too small compared to the overall purchase costs of an electric truck to make much difference.

Since delivery trucks in urban areas can encounter highly variable speeds as routes are being served, it is useful to examine the effect of travel speeds on the overall results. The speeds assumed in the baseline scenario are 40 mph between the depot and service area, and 20 mph within the service area. If these speeds are increased to 50 and 30 respectively, or decreased to 30 and 10, the electric trucks do slightly worse. Electric trucks win in only 20 scenarios if speeds are increased since these trucks are not geared and therefore consume more energy at higher speeds. At lower speeds, they consume significantly less energy, but the time constraint is more often binding and thus the purchase of additional trucks is necessary in more scenarios; at lower speeds, the electric trucks win in only 10 of the 128 scenarios.

The electric trucks also perform slightly better if the service area is uphill of the depot. A theme that emerges from the results here is that whenever more energy is required to serve the route, this is favorable to the electric trucks so long as the additional energy required is not large enough to cause the energy constraint to be binding. Thus, when the route us uphill when the trucks are heaviest and downhill when they're empty, the electric vehicles are best option in four additional scenarios. The energy saved by structuring the route in the opposite configuration is not enough to result in more wins for the conventional truck, however.

6. Sensitivity Analysis and Parameter Elasticity

A sensitivity analysis is useful to understand what factors have the highest impact on per-mile costs. We compute the elasticity of per-mile costs to each factor using the following an arc elasticity formula (18) where η_x^c is the elasticity of per mile cost c to parameter x:

$$\eta_x^c = \frac{(x_1+x_2)/2}{(c_1+c_2)/2} \cdot \frac{\Delta_c}{\Delta_x} = \frac{(x_1+x_2)}{(c_1+c_2)} \cdot \frac{(c_2-c_1)}{(x_2-x_1)} \tag{21}$$

As one might expect, changes in the purchase cost of the truck affect the electric vehicles about twice as drastically as the conventional vehicles, whereas changing other parameters has a much more drastic effect on the conventional vehicle. This reaffirms a theme seen throughout these results: the purchase cost of the electric vehicles is the single most important factor in determining its overall costs. Once the initial capital outlay is made, operating costs are much smaller than the conventional vehicle.

Table 4: Values used to determine elasticities listed in Table 5. Other parameters have the same value as shown in Table 2.

Parameter	Low Value	Medium Value	High Value
Round trip depot-service area distance k_m	20 mi	40 mi	60 mi
Number of customers *n*	20		150
Customer service time t_{cs}	6 min	15 min	30 min
Demand weight w_{cd}	10 lbs	100 lbs	500 lbs
Service Area *a*	25 mi^2	40 mi^2	100 mi^2
Diesel cost	$1.99/gal	$3.97/gal	$5.96/gal
Electricity cost	$0.0552/kWhr	$0.1104/kWhr	$0.1656/kWhr

Table 5: Elasticities for low, medium, and high values of parameters indicated in Table 3. The value shown is the percent change in cost per customer when the value of the indicated parameter is changed by 1%

		n	t_{cs}	w_{cd}	k_2	A	Fuel/Elec Cost	MPG	Disc. Fact	Fuel Inf. Fact	Purchase Cost
Low Values	**N-Series**	0.207	0.078	0.0001	0.224	0.119	0.397	-0.317	-0.169	0.050	0.461
	E-Star	0.022	0	0.0003	0.046	0.019	0.038	0	-0.026	0.005	0.930
	Newton	0.023	0	0.0003	0.048	0.019	0.040	0	-0.027	0.005	0.927
Medium Values	**N-Series**	0.274	0.170	0.002	0.317	0.094	0.521	-0.356	-0.212	0.066	0.324
	E-Star	0.028	0	0.005	0.091	0.021	0.063	0	-0.041	0.008	0.881
	Newton	0.029	0	0.005	0.093	0.021	0.067	0	-0.042	0.008	0.878
High Values	**N-Series**	0.210	0.163	0.007	0.457	0.035	0.530	-0.370	-0.216	0.067	0.309
	E-Star	0.014	0	0.008	0.135	0.005	0.075	0	-0.045	0.009	0.857
	Newton	0.025	0	0.014	0.141	0.009	0.087	0	-0.050	0.011	0.843

Elasticities of ten of the parameters were determined for three different scenarios; the values of the parameters for each scenario are shown in **Table 4**; elasticities are shown in **Table 5**. The number shown is the percentage by which the cost per customer changes for each 1% change in the value of the given parameter. For instance, in the low value scenario, if the purchase cost of the N-Series truck is increased by 1%, the cost per customer increases by 0.461%. Likewise, a negative value indicates an inverse relationship between the given parameter and the total cost.

It is clear that increases in gas mileage do not affect the electric vehicle. Note also that the customer service time will also only affect the conventional truck, as it will burn fuel idling or restarting; the electric vehicle uses no energy during this time. Predictably, gas mileage has an inverse relationship with cost, so as the conventional vehicle's gas economy improves, the cost

per customer decreases. Discount factor has also has an inverse relationship, since as inflation increases, the outlay in present day dollars can be thought of as decreasing. The depot-to-service area distance, fuel/electricity cost, and fuel inflation rate all have positive elasticities that are much greater in magnitude for the conventional truck than for the electric trucks. This is another affirmation that the operating costs of the conventional vehicle comprise a much greater percentage of the total cost than for the electric trucks. This effect is also seen in the elasticities of the other parameters, but to a lesser extent.

7. Breakeven Analysis

A breakeven analysis is also performed for the three scenarios summarized in Table 4. This analysis is performed by replacing the objective function given by (14) with an equation that sets the cost of the conventional truck and the electric truck equal to one another. In this formulation, *j* denotes the N-Series conventional truck and *I* now denotes the set of electric trucks, indexed by *i,* where $i \in \{1,2\}$.

$$c_{tot}^{j} = c_p^j m^j + \sum_{k=1}^{K} (1+f_d)^{-k} \left[(1+f_e)^k c_e^j f(m^j) d_s + c_m^j L(m^j)\right] + c_b^j m^j =$$

$$c_{tot}^{i} = c_p^i m^i + \sum_{k=1}^{K} (1+f_d)^{-k} \left[(1+f_e)^k c_e^i f(m^i) d_s + c_m^i L(m^i)\right] + c_b^i m^i - c_t^i \quad \forall i \in I \tag{22}$$

s.t.

$$\frac{E_{tot}^i}{m^i} \leq E_{bc}^i \; \forall i \in I \tag{23}$$

$$\frac{W_{cd}}{m^{i,j}} \leq W_{pay}^{i,j} \; \forall i \in I, \forall j \in J \tag{24}$$

$$\frac{t_{tot}}{m^{i,j}} \leq t_{max} \tag{25}$$

$$m^{i,j} \geq 0 \tag{26}$$

$$m^{i,j} \in Set\ of\ integers \tag{27}$$

Equation 22 is then satisfied by using one of the following parameters as a decision variable: current diesel price, the conventional truck's gas mileage, the fuel inflation rate, or the current electric truck purchase cost.

A fairly common and intuitive theme that emerges in all of the results is that in order for the electric trucks to outperform the conventional counterparts, the money saved over the lifetime of the electric trucks must be great enough to make up for their significantly higher purchase costs. In order to quantify what might need to happen for this to be a likely outcome, it is useful to quantify the breakeven points for the pertinent parameters. These results are shown in **Table 6.** This table shows each of the separate possible conditions under which the electric truck indicated costs the same as the conventional truck for these parameters. In other words, for the base battery replacement scenario with medium parameter values, the conventional truck and the e-truck will cost the same if the gas mileage of the conventional truck is 5.33 mpg, or the average diesel cost is $6.34 per gallon, or the fuel inflation rate is 12.6%, etc.

Intuitively, it is seen that the breakeven points assuming no battery replacement are much closer to current values than those assuming battery replacement. For instance, while the 5.33 mpg or $6.34 diesel price necessary for the E-Star and N-Series to break even in the base case scenario may be unrealistic, one can easily envision the conventional truck averaging 7.74 mpg or diesel rising to $4.76, as required to break even if there is no battery replacement cost. Additionally, some combination of, say, a slight rise is fuel cost and a slight decrease in e-truck purchase cost would result in a breakeven point. Therefore, while the e-trucks are currently a more expensive option in most situations, a confluence of rising energy costs and falling technology costs could create an environment where electric trucks prevail in far more scenarios.

8. Conclusions

This paper presents a logistical planning model to estimate the competitiveness of new generation trucks. This model is easily adaptable to include new trucks as information on them becomes available, or to tailor to the specific needs of particular routes or carriers since it models (a) energy consumption as a function of distance traveled, speed, and route/vehicle characteristics and (b) key logistical planning parameters such as customer density, demand weight, and depot-to-service area distance.

This research shows that for electric trucks to be competitive, the cost savings from the reduced operational cost must be sufficient to overcome the much higher initial purchase cost of electric trucks. This effect can be heightened when the tighter constraints on electric vehicles lead to the purchase of additional vehicles above and beyond the required number of conventional vehicles.

For electric trucks to be a viable alternative, then, some combination of the following factors must be present:

1. Daily distances travelled are high, approaching the electric trucks maximum range of 100 miles (but the battery energy constraint is not binding).
2. Low speeds or congestion and traffic jams are prevalent in the area of the route.

3. Customer stops are frequent and numerous, and a conventional truck would typically idle during these stops.
4. The trucks are loaded to a high percentage of their capacity
5. The time constraint (rather than the energy or capacity constraints) is binding.
6. Since the electric engine is more energy efficient, grades or other factors exist which cause increased expenditures of energy (but where the battery energy constraint is not binding).
7. The planning horizon is extended beyond ten years.

As early adopters begin to use electric vehicles to serve routes, a number of these factors are clearly present on these routes. For example, Fed Ex, which recently added the small, lite Navistar E-Stars to its fleet, serves routes where numbers 1, 2, 3, 5, and 6 are likely true. Frito Lay recently added the heavier Smith Newtons to its fleet to serve routes where numbers 1, 2, 4, and 6 are prevalent. Increasing fuel costs and reduction in battery costs and other costs associated with the new technology can be expected to lessen the degree to which these favorable factors must be present for electric trucks to be a good alternative.

Table 6: Breakeven points for low, middle, and high scenarios, where parameters are set as shown in Table 4.

A) Low Values

		MPG	Diesel Cost	E-Truck Purchase Cost	Fuel Inflation Rate
Base Battery Replacement	E-Star	2.91	$11.77	$65,235.45	25.0%
	Newton	2.90	$11.81	$64,795.51	25.3%
No Battery Replacement	E-Star	3.97	$8.83	$97,235.45	19.4%
	Newton	3.95	$8.87	$96,795.51	19.6%

B) Medium Values

		MPG	Diesel Cost	E-Truck Purchase Cost	Fuel Inflation Rate
Base Battery Replacement	E-Star	5.33	$6.34	$102,085.38	12.6%
	Newton	5.29	$6.37	$101,417.49	12.8%
No Battery Replacement	E-Star	7.74	$4.76	$134,085.38	6.5%
	Newton	7.67	$4.79	$133,417.49	6.7%

C) High Values

		MPG	Diesel Cost	E-Truck Purchase Cost	Fuel Inflation Rate
Base Battery Replacement	E-Star	2.77	$11.67	$45,076.12	26.5%
	Newton	6.65	$5.40	$116,423.39	9.4%
No Battery Replacement	E-Star	3.52	$9.32	$77,076.12	21.9%
	Newton	9.77	$4.04	$148,423.39	2.9%

References

Beardwood, J., Halton, J.H. & Hammersley, J.M., 1959. The shortest path through many points. *Mathematical Proceedings of the Cambridge Philosophical Society*, 55(04), p.299-327.

Botsford, C. & Szczepanek, A., 2009. Fast Charging vs. Slow Charging: Pros and cons for the New Age of Electric Vehicles. In EVS24, The International Battery, Hybrid and Fuel Cell Electric Vehicle Symposium.

Coyle, M., 2007. *Effects of Payload on the Fuel Consumption of Trucks*, U.K. Department for Transport.

Daganzo, C., 2005. *Logistics systems analysis*, Springer.

Economist, T., 2010. Electric planes: High voltage | The Economist. *The Economist Technology Quarterly*. Available at: http://www.economist.com/node/16295620 [Accessed August 11, 2011].

Electrification Coalition, 2010. *Fleet Electrification Roadmap*, Electrification Coalition.

FedEx, 2010. FedEx Introduces First All-Electric Trucks To Be Used in the U.S. Parcel Delivery Business. *FedEx Global Newsroom*. Available at: http://news.van.fedex.com/node/16470 [Accessed July 29, 2011].

Feng, W. & Figliozzi, M.A., 2011. Conventional vs. Electric Commercial Vehicle Fleets: A Case Study of Economic and Technological Factors Affecting the Competitiveness of Electric Commercial Vehicles in the USA. *City Logistics VII*.

Figliozzi, M.A., 2008. Planning Approximations to the Average Length of Vehicle Routing Problems with Varying Customer Demands and Routing Constraints. *Transportation Research Record: Journal of the Transportation Research Board*, 2089(-1), p.1-8.

Jeeninga, H., van Arkel, W.G. & Volkers, C.H., 2002. *Performance and Acceptance of Electric and Hybrid Vehicles.*, Municipality of Rotterdam, Rotterdam, Netherlands.

Kilcarr, S., 2010. Total ownership cost key to electric truck appeal. *Fleet Owner*. Available at: http://fleetowner.com/green/archive/total-ownership-cost-key-0930/ [Accessed July 29, 2011].

Knipe, T.J., Gaillac, L. & Argueta, J., 2005. *100,000-mile Evaluation of the Toyota RAV4 EV*, Southern Califorrnia Edison.

Langevin, A., Mbaraga, P. & Campbell, J.F., 1996. Continuous approximation models in freight distribution: An overview. *Transportation Research Part B: Methodological*, 30(3), p.163-188.

Mannering, F.L., Washburn, S.S. & Kilareski, W.P., 2008. *Principles of highway engineering and traffic analysis*, Wiley.

Motavalli, J., 2010. Frito-Lay Adds Electric Trucks to Its Fleet. *NYTimes.com*. Available at: http://wheels.blogs.nytimes.com/2010/09/08/frito-lay-adds-electric-trucks-to-its-fleet/ [Accessed July 29, 2011].

Panagiotidis, M., Delagrammatikas, G. & Assanis, D., 2000. Development and Use of a Regenerative Braking Model for a Parallel Hybrid Electric Vehicle. *SAE Transactions*, 109(3), p.1180-1191.

van Rooijen, T. & Quak, H., 2010. Local impacts of a new urban consolidation centre - the case of Binnenstadservice.nl. *Procedia - Social and Behavioral Sciences*, 2(3), p.5967-5979.

Sandalow, D., 2009. *Plug-in electric vehicles: what role for Washington?*, Brookings Institution Press.

Smith EV, 2010. New evidence shows electric vans could last over ten years. *Fleet News*. Available at: http://www.fleetnews.co.uk/news/2010/12/1/new-evidence-shows-electric-vans-could-last-more-than-10-years/38353/ [Accessed July 29, 2011].

USDOE, 2009. Department of Energy - President Obama Announces $2.4 Billion in Grants to Accelerate the Manufacturing and Deployment of the Next Generation of U.S. Batteries and Electric Vehicles. *energy.gov*. Available at: http://apps1.eere.energy.gov/news/news_detail.cfm/news_id=12697 [Accessed July 29, 2011].

Vermie, T., 2002. *Electric Vehicle City Distribution, Final Report.*, European Commission Project.

Acknowledgements

The authors would like to thank OTREC and the Portland State University Faculty Enhancement Grant for funding this research.