Transportation Research Part E 49 (2013) 8–23

Contents lists available at SciVerse ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

A methodology to evaluate the competitiveness of electric delivery trucks

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ARTICLE INFO

Article history:
Received 20 August 2011
Received in revised form 20 June 2012
Accepted 23 June 2012

Keywords:
Urban deliveries
Commercial electric vehicles
Logistical constraints
Real-world speed profiles

ABSTRACT

This paper examines the competitiveness of the latest generation of electric delivery trucks. A new model that integrates routing constraints, speed profiles, energy consumption, and vehicle ownership costs is developed. The model is applied to the study the competitiveness of three commercial vehicles: a widely available conventional diesel truck and two brands of electric trucks. Scenarios and breakeven points are calculated and analyzed for a large number parameter combination. The results show that route feasibility, minimum fleet size, distance traveled, battery life, purchase costs, and planning horizon are among the most significant factors affecting commercial electric vehicle competitiveness.

1. Introduction

Political and practical considerations have produced an environment that is increasingly conducive to a growing presence of electric vehicles. For example, the economic stimulus package enacted in United States (US) in 2009 contained $2.4 billion in the form of Department of Energy 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 electric cars gaining popularity and companies such as Frito Lay, Fed Ex, and Staples introducing electric trucks into fleets (Ramsey, 2010). Other countries such as 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 or even alternative engines and energy sources.

Electric delivery trucks are a relatively new innovation, part of a current generation of electric vehicles made possible by improved battery technology capable of powering delivery trucks with gross vehicle weight ratings in the 10,000–20,000 lb range (Federal Highway Administration Class 3,4, and 5 in the USA) with a range of 80–100 miles. This research aims to quantify the lifetime costs and competitiveness of serving urban, less-than-truckload (LTL) delivery routes with these 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.

This research presents a novel methodology for analyzing the costs of electric delivery trucks along with their conventional counterparts. This methodology is applied to study urban delivery scenarios using values and assumptions that are typical to US cities. This paper uses values for parameters like electricity cost that are current in the US (as of June 2012) and easily obtained from vehicle manufacturers and distribution managers. Since there are at present only a small number of EVs operating, the stress on the electricity grid caused by these vehicles is negligible, and their effects on the cost of electricity are likewise minimal. However, since this paper considers planning horizons as long as 11 years, it is possible

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http://dx.doi.org/10.1016/j.tre.2012.07.003

Table 1
Specifications of three trucks considered in the model.

	Navistar E-Star	Smith Newton	Isuzu N-Series
Price	\$150,000	\$150,000	\$50,000
Battery size	80 kW h	80 kW h	~360 kW h[a]
Stated range	100 miles (161 km)	100 miles (161 km)	~350 miles (564 km)
GVW	12,000 lbs (5442 kg)	16,535 lbs (7499 kg)	12,000 lbs (5442 kg)
Tare	8000 lbs (3628 kg)	9143 (4146 kg)	5672 (2572 kg)
Payload	4000 lbs (1814 kg)	7392 (3352 kg)	6328 (2869 kg)

[a] Battery power equivalent for the conventional truck assumes a diesel energy density of 27.6 kW h/lb and engine efficiency of 30%; calculated by the authors based on figures from: (Economist, 2010).

to envision a scenario where a population of EVs enters the marketplace in that time that effects the price and/or reliability of electricity in the grid. This potential phenomenon is studied by Green et al. (2011) among many other references. The present paucity and slow penetration rate of EVs ensures that these effects will be anticipated by public electric companies. Because of the higher efficiency of EVs relative to conventional trucks and the long-term stability and lower growth of electricity prices in relation to fuel fossil energy sources volatility (Regnier, 2007), it is unlikely that electricity price increases due to this phenomenon would have a large to affect the competitiveness of the EV.

Because at this time there is no cost associated with CO_2 emissions in the US (e.g., a tax or cap-and-trade market) and does not appear to be one in the near future, this research assumes no cost associated with CO_2 emissions until Section 7. The introduction of CO_2 costs (expected in 2013 in the European Union) will favor EVs powered from clean or green energy sources.

This paper is organized into seven sections following this introduction: (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; (3) the methodology section describes the modeling framework employed in the research; (4) data sources are identified; (5) individual truck competitiveness across 243scenarios is considered; (6) elasticity of the parameters considered in the model are found and analyzed; (7) a breakeven analysis that investigates where the EV's become competitive is performed for a middle of the road case; (8) finally, conclusions are presented.

2. Literature review

While the body of research pertaining specifically to electric delivery trucks is fairly young, this research draws upon several streams of literature investigating EV properties and vehicle routing. 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 and Quak (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, 2010) of the lithium ion batteries that power the Smith Newton electric trucks finds that they will retain 80% of their initial capacity after 3000 cycles of fully charging and discharging.

A technology that has been developing in concert with EV's and their batteries is regenerative braking. Using regenerative braking, the EV's battery is able to recover some portion of the vehicle's kinetic energy as it slows. There is a range of values reported in the literature for the percentages of energy that can be recovered via regenerative braking, with Chicurel (1999) reporting that as much as 45% of braking energy is recoverable and Gao et al. (2007) reporting that this number could be as high as 60%, depending on travel speeds and other factors. Gao and Ehsani (2010) also provide a good review of the principles and conclude that the exact amounts that can be recovered vary with travel speeds and other factors.

In terms of charging infrastructure, Botsford and 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. Along these lines, Conrad and Figliozzi (2011) recently analyzed the Electric Vehicle Routing Problem, a special case of the Vehicle Routing Problem (VRP) that takes into account the limited range of EV's and the impact of recharging speed.

A recent report from the US-based Electrification Coalition (2010) provided 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 and Figliozzi (2012) propose a 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 at least 15–30%.

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 2011, 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. In addition, Smith Newton has recently announced the opening of a new EV truck assembly plant in the Bronx (New York) in late 2012 (Motavalli, 2011). 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 best of the authors' knowledge, the integration of a power consumption, real-world speed profiles, routing, and logistics model to compare distinct engine and fuel technologies is a novel contribution to the literature.

3. Methodology

This research integrates four models that are presented in this section: (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 velocity and weight, (c) a continuous approximation model to estimate fleet size, distance traveled, and ensure that practical routing constraints are satisfied, and (d) a method to estimate the additional energy needed to follow real-world travel speed profiles.

3.1. 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. The following mathematical problem identifies the most economical EV.

Indices:

- I = set of electric truck types considered, indexed by i; $i \in \{1, 2\}$.
- K = set of years in planning horizon, indexed by k; $k \in \{1, 2, \ldots, K\}$.

Decision variable:

- m^i = number of trucks of type i to service all the daily customer demands.
- y^i = whether truck type i is used.

Costs:

- c^i_{tot} = total cost for truck i.
- c^i_p = purchase cost for truck i.
- r^i_K = resale value for truck i at year K.
- c^i_e = energy cost for truck i.
- c^i_m = maintenance cost per mile for truck i.
- c^i_b = battery replacement cost for truck i.
- c^i_t = tax incentive for the purchase of truck i.

Inflationary factors:

- f_d = discount factor.
- f_e = rate of inflation in electricity costs.

Other parameters:

- $f(m^i)$ = electricity consumed per day by m^i vehicles.
- d_s = days of service per year.
- $L(m^i)$ = daily distance travelled to serve route by m^i vehicles.
- E^i_{tot} = total fleet energy required, for truck type i fleet, to serve the daily customers.
- E^i_{bc} = battery capacity for truck type i.
- W_{cd} = total daily customer demand.
- W^i_{pay} = payload capacity for truck type i.

- t_{tot} = total time necessary to travel to customer locations and serve customers.
- $t_{\max}$ = maximum permissible route duration.
- b_k^i = whether the battery is replaced in year k for truck type i (binary 0–1 parameter).

$$Minimize \sum_{i \in I} c_{tot}^i \tag{1}$$

where

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

subject to

$$\frac{E_{tot}^i}{m^i} \leqslant E_{bc}^i y^i \quad \forall i \in I \tag{2}$$

$$\frac{W_{cd}}{m^i} \leqslant W_{pay}^i y^i \quad \forall i \in I \tag{3}$$

$$\frac{t_{tot}}{m^i} \leqslant t_{\max} y^i \quad \forall i \in I \tag{4}$$

$$m^i \geqslant 0 \quad \forall i \in I \tag{5}$$

$$m^i \in \text{Set of Integers} \tag{6}$$

$$\sum_{i \in I} y^i = 1 \tag{7}$$

$$y^i \in \{0,1\} \quad \forall i \in I \tag{8}$$

Eq. (2) is the energy constraint, stating that the energy consumed by the electric truck must be less than its battery capacity; Eq. (3) is the cargo constraint, stating that each truck must carry less than its payload capacity, and; Eq. (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 (Eqs. (5) and (6)). Eq. (7) ensures that only one truck type is used, i.e., having a "mixed" fleet is not allowed, while Eq. (8) ensures that y_i is a binary decision variable.

For the conventional truck, an analogous cost minimization model was used where diesel fuel costs and tank capacity are used in lieu of electricity costs and battery capacity. Thus, for the Isuzu N-Series truck (denoted by j), the additional parameters considered are:

- r_K^j = resale value of truck j at year K.
- c_f^j = fuel cost for truck j.
- f_f = rate of inflation in fuel costs.'
- $g(m^j)$ = fuel consumed per day by m^j vehicles.
- F_{tot}^j = total diesel fuel required for conventional truck fleet to serve the daily customers.
- F_{tc}^j = tank capacity for truck j.

The decision variable in this case is:

- m^j = number of conventional trucks to service all the daily customer demands.

All other parameters are the same for both types of trucks, however the tax incentive term is not included for the conventional truck since these are generally not incentivized (although it could easily be included if a situation arose where they were incentivized). There is also no battery replacement cost associated with the conventional truck. The objective function and constraints for the conventional truck are:

$$Minimize\ c_{tot}^j = c_p^j m^j - (1+f_d)^{-K} r_K^j + \sum_{k=1}^{K} (1+f_d)^{-k} [(1+f_f)^k c_f^j g(m^j) d_s + c_m^j L(m^j)] \tag{9}$$

subject to

$$\frac{F_{tot}^j}{m^j} \leqslant F_{tc}^j \tag{10}$$

$$\frac{W_{cd}}{m^j} \leqslant W^j_{pay} \tag{11}$$

$$\frac{t_{tot}}{m^j} \leqslant t_{\max} \tag{12}$$

$$m^j \geqslant 0 \tag{13}$$

$$m^j \in \text{Set of Integers} \tag{14}$$

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 in the Portland metropolitan area.

Costs that are the same for each vehicle (e.g. overhead) are omitted as they do not affect the comparison between the trucks. The objective functions given by Eqs. (1) and (9) could easily be extended to include other costs (e.g., emissions). Since the values of the parameters are assumed to be current US values (where emissions are not presently taxed), it is assumed that there is no cost associated with tailpipe CO_2 emissions; however, the breakeven value for CO_2 emissions are included in Section 7.

Regarding labor costs, this cost item is highly significant. If an additional vehicle and driver is needed, it can be easily shown that EVs are not competitive because with an estimated driver cost of $52,000 per year must be added on top of the higher EV purchase costs.

3.2. Continuous approximation model

We analytically estimate the average cost of serving routes 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 analytical insights about the relationships between parameters and capturing key variables affecting costs (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 (1999) and others; Langevin et al. (1996) provide a comprehensive review of these approximations and their applications.

Beardwood's approximation for the tour distance of a Travelling Salesman Problem (TSP), a one-vehicle instance of the VRP, is given by:

$$L(n) = k_1\sqrt{nA} \tag{15}$$

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. An extension of this is that a tour which originates at a single depot some distance k_2 from the center of the service area has an associated distance that can be approximated by:

$$L(n) = k_1\sqrt{nA} + k_2 m \tag{16}$$

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, 1999). 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. This term corresponds to 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:

$$L(n) = k_1\frac{n-m}{n}\sqrt{nA} + k_2 m \tag{17}$$

The first term again 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, but the inclusion of the $(n - m)/n$ factor in the first term has some useful properties. The value of this term approaches zero as the n approaches m, so its inclusion corrects the overestimation of the local tour distance in when the number of customers served per truck is small. In cases where n is large relative to m, the first term tends toward the model proposed by Beardwood. Thus, provided the assumptions regarding

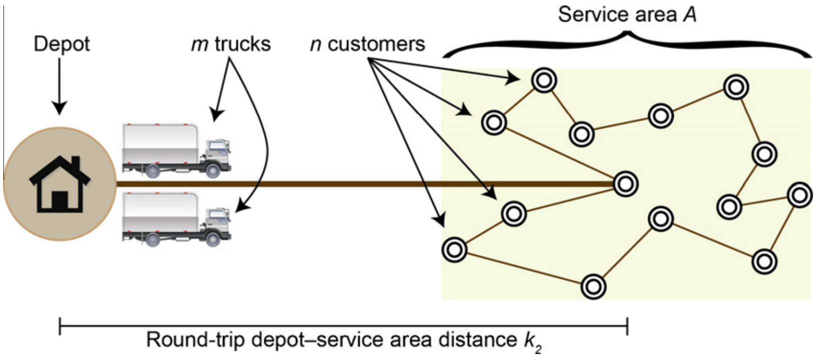

Fig. 1. Illustration of the configuration of the vehicle routing problem considered in this research.

known customer demands and a fairly high depot distance hold, this model provides a good approximation of tour length. This configuration is illustrated in Fig. 1.

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.

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:

$$D_a = \frac{1}{2}k_2 \tag{18}$$

The truck weight W_a is given by:

$$W_a = W_t + \frac{W_{cd}}{m} \tag{19}$$

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:

$$D_b = k_1 \frac{n-m}{n}\sqrt{An} \tag{20}$$

$$W_b = W_t + \frac{W_{cd}}{2m} \tag{21}$$

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

$$D_c = \frac{1}{2}k_2 \tag{22}$$

$$W_c = W_t \tag{23}$$

This model 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, 2009); the addition of time window constraints leads to less efficient routes and bigger fleets since on average less customers can be served per route/vehicle.

3.3. 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, a diesel truck for which the researchers had access to fuel efficiency data from a local company. The properties of these trucks are shown in Table 1. While the weight ratings of the three trucks are fairly similar, 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 accelerate, to overcome aerodynamic and rolling resistance, and to navigate grades. The amount of energy into accelerate the truck to a velocity v (in ft/s [m/s]) is simply equal to the change in the kinetic and gravitational potential energy of the truck divided by the efficiency of the vehicle:

$$E_{acc} = \frac{\frac{1}{2}Mv^2 + W\Delta h}{eff_{tot}} \tag{24}$$

where M is the mass of the truck in slugs (kg), determined by dividing the weights obtained from Eqs. (19), (21), and (23), by the gravitational constant g = 32 ft/s^2 (9.8 m/s^2), and Δh is the change in height in feet (meters) encountered during this acceleration. The term in the denominator, eff_{tot}, takes into account both the engine efficiency eff_{eng} and the efficiency of the charging process eff_{chg} (energy is lost when the battery is recharged):

$$eff_{tot} = eff_{eng} \times eff_{chg} \tag{25}$$

Mannering et al. (2008) present a good summary and discussion of equations needed to estimate the power consumption of a vehicle moving at a velocity v_{avg}:

$$P = \frac{\rho C_D A_f v_{avg}^3}{2} + f_{rl} W v_{avg} + G_{avg} W v_{avg} \tag{26}$$

where P is the power consumed in ft-lbs/s (W), ρ is the air density in slugs/ft^3 (kg/m^3), C_D is the coefficient of drag (unit-less), A_f is the frontal area of the vehicle in ft^2 (m^2), G_{avg} is the average grade of the roadway as a percentage, and W is the weight of the vehicle in lbs (N). The rolling resistance coefficient, f_{rl}, is a function of the vehicle's velocity:

$$f_{rl} = 0.01\left(1 + \frac{v_{avg}}{147}\right) \tag{27}$$

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

$$E_{res} = \left(\frac{\rho C_D A_f v_{avg}^3}{2} + f_{rl} W v_{avg} + G_{avg} W v_{avg}\right) \times t/eff_{tot} \tag{28}$$

If the speed for leg 'a' of the route is v_a, the speed for leg 'b' is v_b, and the speed for leg 'c' is v_c, it is then possible to estimate the total energy consumed by traveling the route by combining Eqs. (24) and (28) with the corresponding components of Eq. (17). Assuming constants speeds in each leg and 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:

$$E_{tot} = f(m) = \frac{1}{eff_{tot}} \left\{ \begin{array}{l} \left(\frac{1}{2}M_a v_a^2\right)m + \left(\frac{\rho C_D A_f v_a^3}{2} + f_{rl} W_a v_a + G W_a v_a\right) \frac{k_m m}{2 v_a} \\ \left(\frac{1}{2}M_b v_b^2\right)n + \left(\frac{\rho C_D A_f v_b^3}{2} + f_{rl} W_b v_b + G W_b v_b\right) \left(\frac{k_1 \frac{n-m}{n} \sqrt{An}}{v_b}\right) \\ +\left(\frac{1}{2}M_c v_c^2\right)m + \left(\frac{\rho C_D A_f v_c^3}{2} + f_{rl} W_c v_c + G W_c v_c\right) \frac{k_m m}{2 v_c} \end{array} \right\} \tag{29}$$

From here, it is possible 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.

3.4. Adjustment for real-world velocity profiles

The methodology above assumes that the trucks accelerate uniformly to an assumed constant speed that can be maintained until the next stop. Real world driving conditions can of course deviate significantly from these constant speed assumptions. It is useful, then, to quantify the impact of driving conditions and gain insights about the impacts of factors such as congestion.

The well-known MOVES model developed by the US Environmental Protection Agency (2009) gives velocity–time curves for vehicles on several types of facilities (Koupal, 2010). These curves are widely available and provide a second-by-second descriptions of typical speed profiles for vehicles on different types of facilities. For medium duty vehicles, the model provides eleven velocity–time curves in total, six of which apply to non-freeway roadways while the remaining five apply to freeways. As an example, Fig. 2 shows the velocity–time curve corresponding to drive schedule #204, which describes a medium truck on a non-freeway with an average speed of 20.8 mph (9.3 m/s).

Since analytical function of speed as a function of time are not provided, a second by second numerical integration of the equations presented before is performed to estimate the energy consumption using a MOVES drive cycle. Thus, the acceleration energy consumed during time Δt is given by:

$$E_{acc}(t) = \left(\frac{1}{2}M\Delta v^2(t) + W\Delta h(t)\right) \times \Delta t/eff_{tot} \tag{30}$$

where $\Delta v(t)$and $\Delta h(t)$ are now the changes in velocity and height experienced during second Δt, as given by:

$$\Delta v(t) = v(t) - v(t - \Delta t) \tag{31}$$

$$\Delta h(t) = h(t) - h(t - \Delta t) \tag{32}$$

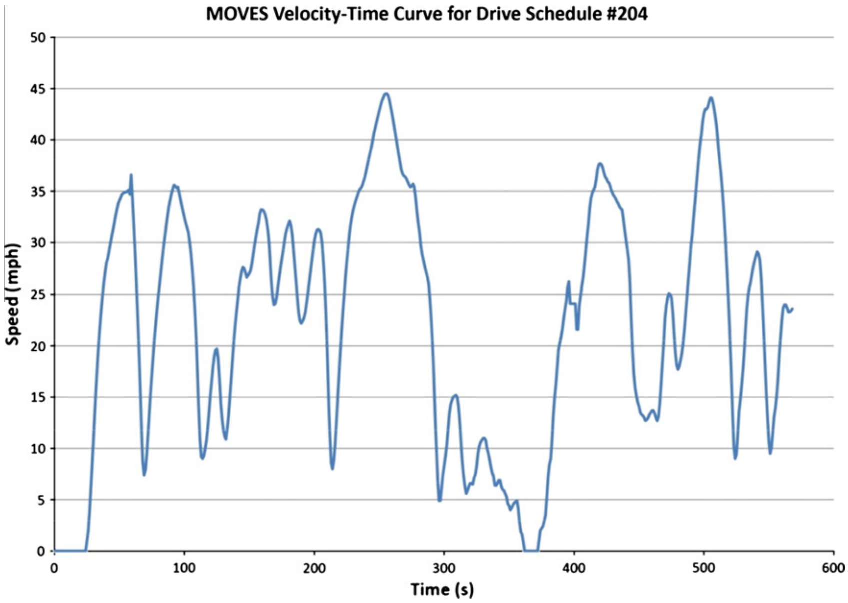

Fig. 2. MOVES Drive Schedule #204 Velocity–Time Curve – average speed 20 mph. *Source*: US EPA (2009).

Similarly, the energy required to overcome resistances met from time $t - \Delta t$ to t can be found by replacing the averaged quantities in Eq. (28) with instantaneous quantities (or, to be precise, second-by-second averages):

$$E_{res}(t) = \left(\frac{\rho C_D A_f \bar{v}^3(t)}{2} + f_{rl} W \bar{v}(t) + \bar{G}(t) W \bar{v}(t)\right) \times \Delta t / eff_{tot} \tag{33}$$

where

$$\bar{v}(t) = v(t - \Delta t) + \frac{v(t) - v(t - \Delta t)}{2} \tag{34}$$

$$\overline{G}(t) = g(t - \Delta t) + \frac{g(t) - g(t - \Delta t)}{2} \tag{35}$$

Since some electric vehicles have some regenerative braking ability, it is also necessary to quantify the kinetic energy lost when the truck decelerates, a portion of which will return to the battery. Hence:

$$E_{dec}(t) = \frac{1}{2} M \Delta v(t)^2 \Delta t \tag{36}$$

when $v(t) < v(t - \Delta t)$ and 0 (zero) otherwise

If a certain percentage eff_{rb} of the energy given by Eq. (36) returns to the battery via regenerative braking, the energy recovered through this mechanism during second t can be written as:

$$E_{rec}(t) = eff_{rb} E_{dec}(t) \tag{37}$$

The second-by-second components are then summed to obtain a value for the total energy spent.

For each of the 11 medium duty MOVES drive schedules, the total energy expended by the truck is given by:

$$E_{tot} = \sum_{t=1}^{T} \{E_{acc}(t) + E_{res}(t) - E_{rec}(t)\} \tag{38}$$

The index t in Eq. (38) represents each second of the velocity–time curve, with T being the total number of seconds for that curve. This result is then compared to the energy spent by the vehicle assuming that it accelerates once to the average speed v_{avg} for a given curve and moves up to a time T-see Eq. (38):

$$E_{avg} = \frac{1}{eff_{tot}} \left\{ \frac{1}{2} M v_{avg}^2 + W \Delta h + T \left(\frac{\rho C_D A_f v_{avg}^3}{2} + f_{rl} W v_{avg} \right) \right\} \tag{39}$$

The ratio found by dividing the result from Eq. (38) using a time-velocity curve l by the result using the average speed of the time velocity curve l yields an energy expenditure or velocity profile coefficient for vehicle type i, VPC(l,i). The coefficient

Table 2
VPCs for six medium duty MOVES velocity–time curves.

MOVES drive schedule ID	Average speed (mph)	Drive schedule name	VPC(l,i) (E-Star)	VPC(l,i) (Newton)	VPC(l,i) (N-Series)
203	15.6	MD 15 mph non-freeway	1.326	1.283	1.362
204	20.8	MD 20 mph non-freeway	1.329	1.287	1.359
205	24.5	MD 25 mph non-freeway	1.307	1.264	1.328
251	34.4	MD 30 mph freeway	1.292	1.260	1.308
252	44.5	MD 40 mph freeway	1.182	1.165	1.191
253	55.4	MD 50 mph freeway	1.044	1.039	1.046

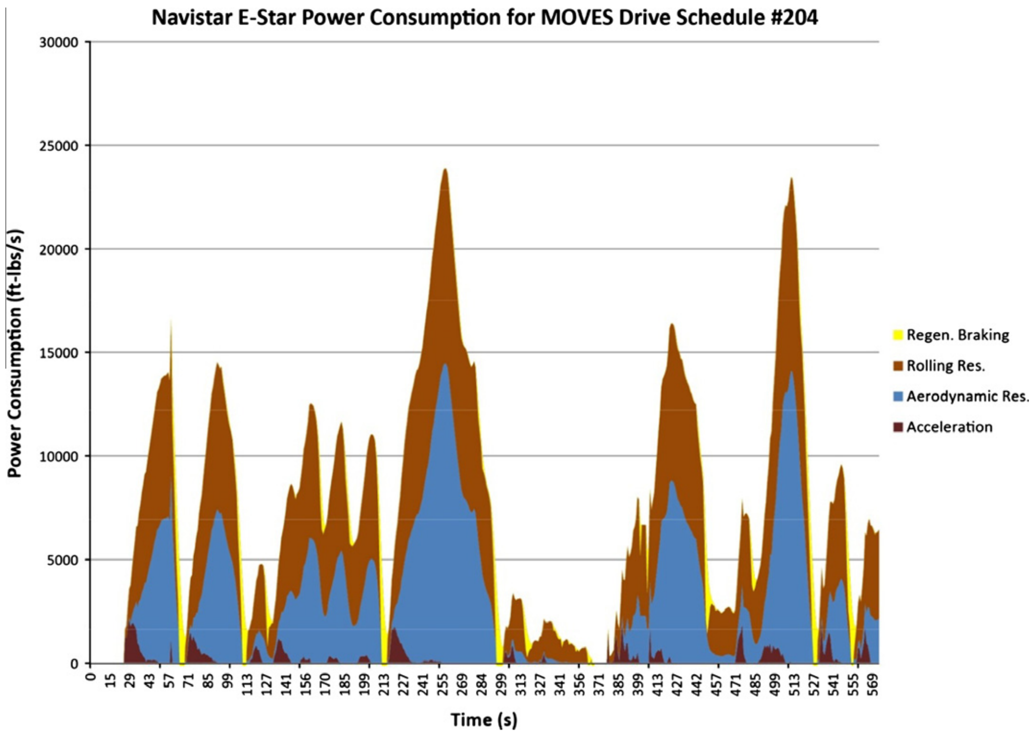

Fig. 3. Power consumption of the Navistar E-Star for MOVES Drive Schedule #204.

VPC(l,i) represents the increase in energy required by following the realistic time-velocity profile l versus simply maintaining the time-velocity profile average speed. Each vehicle type has its own VPC since mass, area and resistance coefficients may differ across vehicle types. Assuming a vehicle weight, herein equal to the tare plus one-half the payload capacity, and using individual vehicle characteristics VPC(l,i) values can be calculated for any of the MOVES drives schedules and vehicle types. These values, shown in Table 2, provide clear insights about the effects of congestion on relative power consumption.

Fig. 3 graphs the power consumption of the Navistar E-Star for drive schedule #204, showing the proportions of the total power used for accelerating, and overcoming aerodynamic and rolling resistances, as well as the power returned to the battery via regenerative braking. The area under this curve represents the energy consumed, with each shaded area representing the energy consumed for that purpose (or returned to the battery, in the case of regenerative braking).

Contrasting the results found using the three legged, average speed energy consumption model described above with those found using the MOVES velocity–time curve model is useful for gleaning information about how traffic conditions and operational parameters affect the head-to-head comparison between the truck types, and it is shown that the stops and starts encountered in real world driving are less important than the assumed speeds (or MOVES drive schedules) that the truck travels.

To gain an understanding of the practical efficiency of the truck types for moving freight, it is useful to calculate the ratio of energy spent per payload-distance (e.g. Joules per kg-km). These ratios are shown in Table 3 for the six MOVES velocity–time curves considered previously. Two cases are tabulated: each truck loaded to its full capacity and a low payload utilization assuming a constant payload weight of 454 kg (1000 lbs or 1 ton). Unsurprisingly, the more efficient EVs provide better ratios of energy spent per payload-distance. For all truck types the energy required to move one kilogram one kilometer increases with the travel speed of the truck. The ratios are more sensitive to travel speed when the trucks are carrying lower

Table 3
Energy spent per kilometer per kilogram for each truck loaded to 50% and 100% of capacity for six medium duty MOVES drive cycles.

MOVES drive schedule ID	Drive schedule name	J/kg km (454 kg cargo)			J/kg km (100% capacity)		
		E-Star	Newton	N-Series	E-Star	Newton	N-Series
203	MD 15 mph non-freeway	1189	1292	2656	365	253	1009
204	MD 20 mph non-freeway	1365	1469	3101	410	278	1150
205	MD 25 mph non-freeway	1541	1647	3557	455	303	1297
251	MD 30 mph freeway	2021	2133	4789	579	374	1695
252	MD 40 mph freeway	2472	2588	5971	694	438	2074
253	MD 50 mph freeway	2937	3058	7183	814	505	2464

payload weights than when they are full to capacity. Between the electric trucks, the Newton offers better ratios when filled to capacity owing to the fact that it has a much greater capacity than the E-Star. By contrast, the E-Star is slightly more efficient by this metric when carrying a small payload due to its smaller tare weight. The ratios for the electric trucks are less sensitive to travel speed than those for the conventional truck.

These changes in efficiency are important and significant; companies are now marketing drive systems, based one type of truck chassis, which allow companies to tailor costs, battery size, engine power, and torque to meet their route requirements more efficiently (ENOVA, 2012).

4. Data assumptions and battery scenarios

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 4. This table also indicates the assumed values and sources for the parameters used in the calculations that follow.

A key component of the financial analysis regards the cost of 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, with the batteries still functioning well (though measurably weaker) after the vehicle surpassed the 100,000 mark. The Electrification Coalition reports a similar lifespan, anticipating a battery lifespan equivalent to about 150,000 miles (Electrification Coalition, 2010). 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 3000 cycles (Smith, 2010) of fully discharging and recharging the battery (more than 11 years at 260 operational days/year). If true, the battery would not need to be replaced during the10-year planning horizon.

Using these results along with projections from Kilcarr (2010) and the Electrification Coalition (2010), we assume three scenarios: (i) with a 100% probability a battery replacement is needed after 150,000 miles at a future cost of \$600/kW h. The alternative scenario (ii) assumes that with a 50% probability a battery replacement is needed after 150,000 miles at a future cost of \$400/kW h with a 50% probability the battery lasts over the planning horizon. Finally, we consider scenario (iii) that assumes that with a 50% probability a battery replacement is needed after 150,000 miles at a future cost of \$200/kW h and with a 50% probability the battery lasts over the planning horizon.

Given current battery costs – in the \$600 to \$800/kW h range – and the fast evolution of battery technology, it is clear that for scenario (i) we are using a somewhat conservative approach in terms of battery costs and replacement whereas scenario (ii) is highly realistic and plausible and scenario (iii) is somewhat optimistic.

Regarding resale values, there is a lot of uncertainty regarding future depreciation for EVs. We assume that after 10 years of utilization both vehicle types have a resale value that is equal to 20% of their original purchase price – a conservative assumption.

5. Results and analysis

Different route instances are built including low, medium, and high values for five parameters—the number of customers, the service area, the depot-service area distance, the customer service time, and the customer demand weight. These values, listed in Table 4, lead to 243 (3^5) different instances as each of the combinations was considered. The cost per customer of serving each route is calculated and the truck type than can serve the route for the lowest cost is declared the "winner" and reported in Table 5.

It is notable that the speed profile does not affect significantly the competitiveness of the EVs since the factors are fairly similar across vehicle types. In both cases (MOVES or constant speed profiles) the EVs win a total of 6 instances. However, battery replacement time and cost do have a significant impact; with battery scenario (i) the conventional truck is the best option in all instances but in battery scenario (iii) the E-Star wins in 32 scenarios and the Newton in 1.

Tax incentives (a \$20,000 tax credit per truck up to 10 trucks) and time horizons are also significant since they decrease the negative impact of high EV's purchase costs. Slow speeds favor and longer route durations favor the EVs but grades

Table 4
Low, medium and high values for the 128 scenarios.

Parameter	Low value	Medium value	High value
Round trip depot-service area distance k_2[a]	20 miles (32 km)	40 miles (64.4 km)	60 miles (97 km)
Number of customers n[b]	20	50	150
Customer service time t_{cs}[c]	6 min	15 min	30 min
Demand weight w_{cd}[d]	10 lbs (4.5 kg)	100 lbs (45.4 kg)	500 lbs (226.8 kg)
Service area a[e]	25 miles^2 (64.7 km^2)	40 miles^2 (103.6 km^2)	100 miles^2 (259.0 km^2)
Diesel cost[f]		$4.07/gal ($1.07/L)	
Electricity cost[g]		.1106/kW h	
Air density ρ[h]		0.002378[a] slugs/ft^3 (1.2256) kg/m^3	
Drag coefficient C_D[h]		0.7	
Frontal area A_f[i]		50 ft^2 (4.65 m^2)	
EV engine efficiency[j]		0.8	
EV charging efficiency[j]		0.8	
Conventional engine efficiency		0.3	
Regenerative braking potential[j,k,l,m]		0.2	
Average speed within service area[n]		44.5 mph (19.9 m/s)	
Average speed depot to SA and back[o]		20.8 mph (9.3 m/s)	
Maintenance costs[p]		$0.20/miles ($0.32/km)for conventional vehicle	
$0.10/mi ($0.16/km)for electric vehicle			
Battery replacement cost[q]		Scenario (i), $600/kW h battery replaced in 7.5 years	
Time constraint[r]		9 h	
Diesel truck base MPG[s]		10 mpg (4.25 km/l)	
Discount factor[t]		6.5%	
Fuel inflation rate[t]		2.5%	

[a] 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.
[b] Low value intended to simulate a Staples- or Frito Lay-type customer load; high value intended to simulate a FedEx-type customer load.
[c] 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.
[d] Low value intended to simulate a FedEx-type demand weight; high value intended to simulate a Staples- or Frito Lay-type demand weight.
[e] Low value is approximately the size of Portland's CBD; high value is approximately the area within Portland city limits.
[f] Average nationwide diesel prices current as of this writing per USDOE [http://www.eia.doe.gov/oog/info/gdu/gasdiesel.asp, retrieved on February 29, 2012].
[g] Electricity prices, averaged across sectors nationally, as of this writing per USDOE [http://www.eia.doe.gov/electricity/epm/table5_6_b.html, retrieved on February 29, 2012].
[h] Mannering et al. (2008).
[i] Assumes approximately 7 ft wide by 7 ft high frontal projection.
[j] Shah (2009).
[k] Panagiotidis et al. (2000).
[l] Gao et al. (2007).
[m] Chicurel (1999).
[n] Average speed of MOVES drive schedule #252.
[o] Average speed of MOVES drive schedule #204.
[p] Motavalli, 2010.
[q] Scenario (i) discussed in data sources section.
[r] Typical time constraint for logistics problems.
[s] From data for Isuzu N-Series trucks.
[t] Feng and Figliozzi (2012).

(assuming a 5% grade from depot-to-service area and −5% grade returning and vice versa) did not alter significantly the results.

Fig. 4 shows the number of instances each truck wins assuming battery replacement scenario (iii) and offers some insights into the effect the logistical parameters on EV competitiveness. The bottom, middle, and top portions of each bar correspond to the number of scenarios the given truck wins when the indicated parameter takes its low, middle, and high values, respectively. The sum of the three parts of each bar is equal to the total number of the 243 scenarios that the given truck wins. Fig. 4a shows the instances in which the N-Series is the best option (i.e., "wins"), Fig. 4b shows the scenarios in which the E-Star is the best option, and Fig. 4c shows the scenarios in which the Newton is the best option.

The greatest variation is seen with the demand weight (w_{cd}) and the round trip depot-service area distance (k_2). Lower demand weights favor the EV (with lower energy consumption battery capacity is not a binding constraint). Regarding round trip distances (k_2), the EV wins in 25 instances with long distance (60 miles) in 7 with medium distance (40 miles) and just in one with small distance (20 miles). This owes to the fact that the purchase costs of the electric trucks constitute a large majority of their overall operating costs whereas fuel costs are a majority for the conventional truck (see Fig. 5); on a per mile basis, the EV has significantly lower marginal costs. A similar relationship is therefore seen with the service area size (parameter a) and number of costumers (parameter n) because route distance is positively correlated with service area and number of customers.

Table 5
Scenarios outcomes.

		N-Series wins	E-Star wins	Newton wins
Speed profile	MOVES speed profiles (base instance)	237	4	2
	Constant speed (3-legs)	237	5	1
Battery replacement	Battery scenario (i)	243	0	0
	Battery scenario (iii)	210	32	1
Tax incentives	No incentive	243	0	0
	Heavily incentivized[2]	228	14	1
Time horizon	9 yrs	243	0	0
	11 yrs	228	14	1
Speed/facility	Fast (drive schedules 205 and 253)	243	0	0
	Slow (drive schedules 203 and 251)	233	9	1
Time constraint	8 h	239	3	1
	10 h	235	7	1
Grade	Upward from depot	242	1	0
	Downward from depot	241	2	0

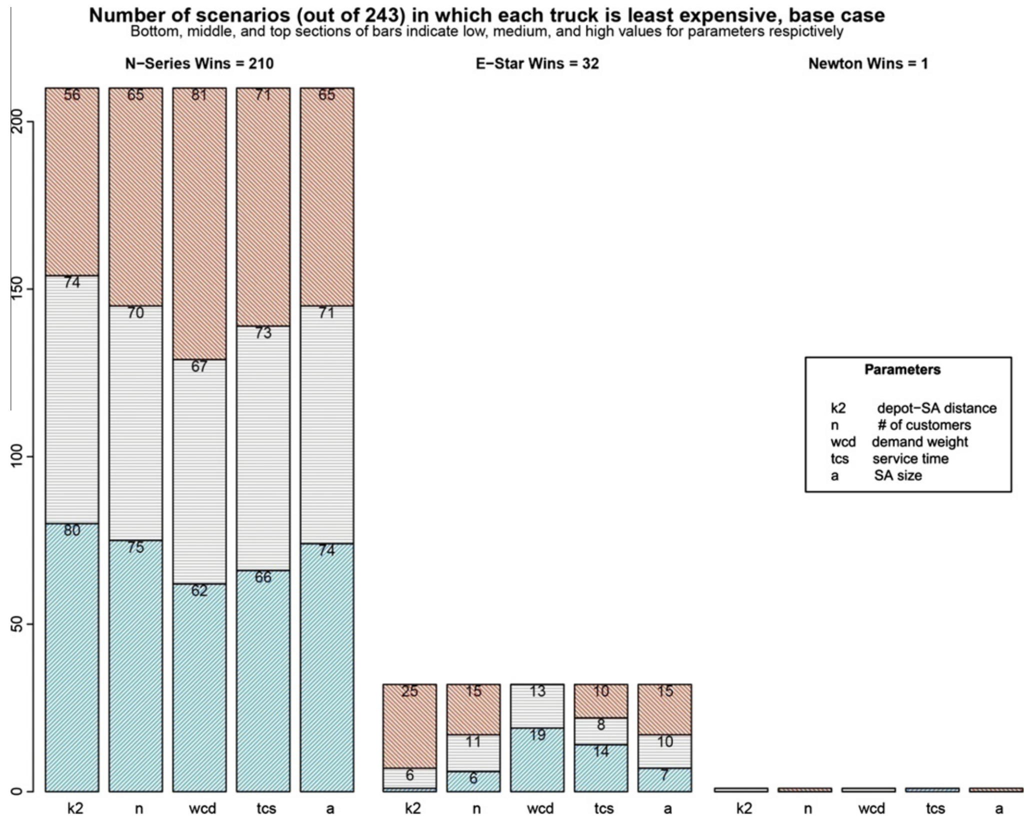

Fig. 4. Number of the 243 scenarios in which each truck is the least expensive option assuming battery replacement scenario (iii).

Fig. 5 shows the relative costs by category for the three trucks assuming that the parameters take the values shown in the middle column of Table 4. It is clear that the EVs can be competitive only if the vehicles are used enough to compensate the higher purchasing costs by the lower per mile operating costs. Fuel costs are responsible for the largest share of conventional trucks ownership costs whereas purchase costs account for the largest share of EVs costs.

6. Elasticity results

A sensitivity analysis is useful to understand what factors have the highest impact on a per-mile cost basis. 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:

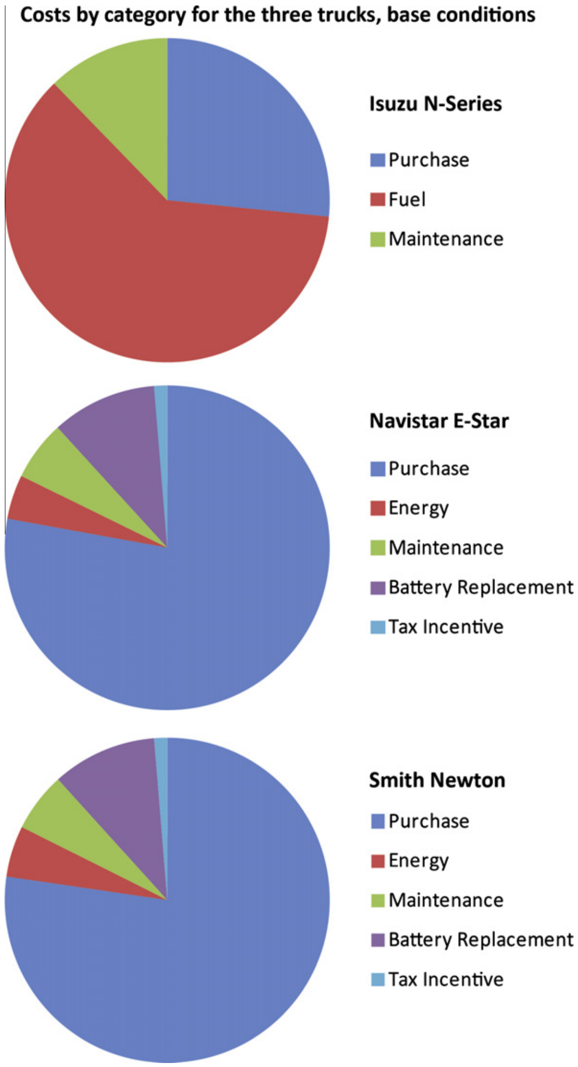

Fig. 5. Proportion of total lifetime costs by category.

Table 6
Elasticity results.

	n	w_{cd}	k_2	A	Fuel/elec. cost	Disc. fact	Fuel/elec. inf. fact	Purchase cost
N-Series	0.269	0.0024	0.339	0.097	0.566	−0.215	0.072	0.300
E-Star	0.023	0.0041	0.071	0.017	0.045	−0.032	0.006	0.799
Newton	0.026	0.0044	0.072	0.020	0.052	−0.034	0.007	0.793

$$\eta_x^c = \frac{(x_1 + x_2)/2}{(c_1 + c_2)/2} \cdot \frac{\Delta_c}{\Delta_x} = \frac{(x_1 + x_2)}{(c_1 + c_2)} \cdot \frac{(c_2 - c_1)}{(x_2 - x_1)} \quad (40)$$

The elasticity of eleven of the parameters shown in the middle column of Table 4 are presented in Table 6. For instance, if the purchase cost of the N-Series truck is increased by 1%, the cost per customer increases by 0.339%. Likewise, a negative value indicates an inverse relationship between the given parameter and the total cost. As expected, purchase cost has the highest elasticity for EVs whereas fuel cost and distance traveled have the highest elasticity values for the conventional diesel truck. 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.

The discount factor has a negative elasticity and it is much greater in magnitude for the conventional truck than for the electric trucks since future operational costs for the conventional vehicle comprise a much greater percentage of the total costs.

7. Breakeven analysis

A breakeven analysis is also performed for the three battery replacement scenarios and the parameters presented in the middle column of Table 4. Breakeven values are found by replacing the objective function with an equation that sets the cost of the electric truck – expression (1) – and the conventional truck – expression (9) – equal to one another. Eq. (41) is then satisfied by using one of the following parameters (ceteris pabirus) as a decision variable: the conventional truck's base gas mileage, current diesel price, the current electric truck purchase cost, the tax incentive per truck, the rate of inflation in energy prices, or the price per ton of carbon dioxide. In this formulation, j denotes the N-Series conventional truck and I denotes the set of electric trucks, indexed by i, where $i \in \{1, 2\}$.

$$c^{j}_{tot} = c^{i}_{tot} \tag{41}$$

subject to

$$\frac{E^{i}_{tot}}{m^{i}} \leqslant E^{i}_{bc} \quad \forall i \in I \tag{42}$$

$$\frac{W_{cd}}{m^{i,j}} \leqslant W^{i,j}_{pay} \quad \forall i \in I, \quad \forall j \in J \tag{43}$$

$$\frac{t_{tot}}{m^{i,j}} \leqslant t_{\max} \tag{44}$$

$$m^{i,j} \geqslant 0 \tag{44}$$

$$m^{i,j} \in \text{Set of integers} \tag{45}$$

The points at which the cost of the conventional and each electric truck are equal so as to satisfy Eq. (41) are termed "breakeven points" and are shown in Table 7. 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. For example, for the base battery replacement scenario (ii), the conventional and the E-Star truck will have the same discounted costs over the planning horizon if the gas mileage of the conventional truck is 7.61 mpg, or the average diesel cost is $4.99 per gallon, or the fuel inflation rate is 6.56%, etc.

It is readily seen that the breakeven points assuming scenario (iii) are much closer to current values than those assuming scenario (i). The breakeven points in the scenario (iii) are very close to today's values or even below some of them; for example, diesel prices as of March 2012 are over $4.1 in many US states. Additionally, some combination of, say, a slight rise is fuel cost and a slight decrease in e-truck purchase cost would result in more favorable breakeven points. Therefore, while the e-trucks are currently a more expensive option in most situations, it is plausible that a confluence of rising energy costs and falling battery costs can create an environment where electric trucks prevail in far more scenarios.

Because at this time there is no cost associated with CO_2 emissions in the US (e.g., a tax or cap-and-trade market) and does not appear to be one in the near future, this research assumes no cost associated with CO_2 emissions until this Section. Breakeven CO_2 costs for tailpipe emissions are reported in this section assuming no carbon footprint for the electricity that powers EVs. It is clear that CO2 costs do not significantly influence the competitiveness of EVs. A more accurate estimation of CO_2 costs using a "wells-to-wheels" methodology will not affect this basic finding and is left as a topic for future research.

Table 7
Breakeven points for three battery replacement scenarios.

		Base MPG	Diesel cost	E-truck purchase cost	Additional tax incentive per truck	Fuel inflation rate (%)	CO_2 price per ton
Scenario (i)	E-Star	6.83	$5.43	$118,824	$31,176	8.1	$100
	Newton	6.74	$5.49	$117,444	$32,556	8.3	$104
Scenario (ii)	E-Star	7.61	$4.99	$128,904	$21,096	6.5	$68
	Newton	7.49	$5.05	$127,524	$22,476	6.7	$72
Scenario (iii)	E-Star	9.86	$4.11	$149,064	$936	2.7	$2
	Newton	9.67	$4.17	$147,684	$2,316	3.0	$8

8. Conclusions

The contributions of this paper to the literature are a new model and methodology for evaluating the relative cost of electric and conventional trucks and new insights into the factors that affect the competitiveness of commercial EVs. Unlike previous research efforts, one model jointly evaluates the implications of routing constraints, route parameters, vehicle characteristics, and ownership costs; four models are integrated: (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 velocity and weight, (c) a continuous approximation model to estimate fleet size, distance traveled, and ensure that practical routing constraints are satisfied, and (d) a model to estimate the energy needed to travel using real-world travel speed profiles.

A novel contribution of this research is also the evaluation of a wide range of scenarios to better understand the impact of routing constraints, electric vehicle characteristics, and traffic/driving environment on the relative costs of electric and conventional commercial vehicles. The model and analysis are easily adaptable to include new trucks as information on them becomes available, or to tailor to the specific needs of particular routes or carriers, because the model includes key cost relationships and parameters based on universal physics and logistics relationships: energy consumption as a function of distance traveled, speed, and route/vehicle characteristics and key logistical planning parameters such as route length and fleet size as a function of 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 significantly higher initial purchase costs. Electric vehicles are not competitive if routing constraints lead to the purchase of additional vehicles above and beyond the required number of conventional vehicles. If fleet size does not change, then EV purchase prices, fuel price, projections about battery costs and lifetimes, and vehicle utilization are the key factors that determine the competitiveness of electric trucks.

The results provide new insights regarding the truck characteristics and logistical constraints that determine whether a conventional or electrical truck is more cost effective. The ownership cost elasticity indicate that the addition of more customers, energy cost increases, or longer distance travelled greatly benefits the electric vehicles (i.e. EV cost elasticity with respect to customers served and energy costs are ten times smaller than the respective diesel vehicle elasticity). On the other hand, diesel vehicle purchase costs or payload elasticity with respect to total costs are roughly ½ the cost elasticity of the respective electric vehicles elasticity (i.e. conventional vehicle costs are less affected by increases in vehicle purchase price or payload per customer). The analysis of breakeven points for three distinct scenarios (combining different battery life and replacement costs) indicates that although EVs are currently a more expensive option in most situations it is highly plausible that a confluence of rising energy costs and falling battery costs will create an environment where EVs will prevail in most scenarios.

In the current environment, 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. 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).
5. The purchase price is reduced by tax incentives or technological breakthroughs.
6. 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 factor numbers 1, 2, 3, 5 and 6 are prevalent. Frito Lay recently added the heavier Smith Newton EV to its fleet to serve routes where factor numbers 1, 2, 4, 5 and 6 are prevalent. A reduction in purchase prices, battery costs, or range limitations can be expected to lessen the degree to which these favorable factors must be present for electric trucks to be a good alternative.

Acknowledgements

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

The authors acknowledge valuable comments and suggestions from anonymous reviewers. Any errors or shortcomings are the sole responsibility of the authors.

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