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An economic and technological analysis of the key factors affecting the competitiveness of electric commercial vehicles: A case study from the USA market

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ABSTRACT

Electric commercial vehicles' (ECVs) energy costs are almost four times less expensive than conventional diesel trucks, on a per-mile basis, at current USA market values. However, ECVs are approximately three times more expensive in terms of vehicle purchase costs. In addition, electric vehicles are simpler and cheaper to maintain there are more uncertainties associated to the life and long-term costs of the ECV batteries. Furthermore, there are limitations in terms of miles driven per day without recharging. These economic and technological tradeoffs motivate this research. Utilizing a fleet replacement optimization framework, a wide range of scenarios, and current USA market data this research finds the key economic and technological breakeven values where ECVs become competitive against conventional diesel counterparts. The results clearly indicate that only in scenarios with high utilization (over 16,000 miles per year per truck) the electric vehicles are competitive, this is especially valid if a battery replacement is not required before the electric commercial vehicle is replaced. The breakeven analysis results show that a 9–27% ECV price reduction can greatly increase their competitiveness when vehicles are driven over 12,000 miles per year.

1. Introduction

Electric commercial vehicles (ECVs) are seen by many governments, environmental friendly groups and organizations as a potential solution to address the impact of commercial vehicles' noise, pollution, and GHG emissions in urban areas, and to address the impact of oil dependence on the USA economy and security (O'Connor, 2011). The 2009 economic stimulus package in the United States contained \$2.4 billion in the form of Department of Energy (DOE) grants to "accelerate the manufacturing and deployment of the next generation of US batteries and electric vehicles (USDOT, 2009). However, high purchase cost and range anxiety are the two main potential barriers for fleet operators to adopt ECVs (EC, 2010).

ECVs have the advantages of high efficient use of energy and less maintenance cost due to the use of electric motor. However, it is not clear if ECVs are a viable solution given the large operational, logistics, and economic differences between ECVs and conventional diesel vehicles. In addition, the ECVs technology and economic characteristics are evolving more rapidly than the well-known and proven diesel technology. In order to minimize the total fleet cost, carriers need to have a good understanding of vehicle performance and cost structure to provide accurate inputs for the optimization model. Although this is usually the case for conventional diesel vehicles, there is a high degree of uncertainty associated to electric vehicle

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battery performance and costs. To deal with these uncertainties we analyze several scenarios and provide a detailed sensitivity analysis.

A fleet vehicle replacement optimization framework requires three types of inputs: economic factors, vehicular characteristics, and initial fleet configuration. Economic factors include planning time horizon, annual number of vehicles (demand) or annual miles that have to be traveled, discount rate, energy price and forecast in the future (fuel, electricity). Vehicular factors include types of new commercial vehicle candidates, and for each vehicle type, the maximum physical life, capital cost and its salvage value function over age, energy efficiency (fuel economy or electricity efficiency) as a function of age, operating and maintenance (O&M) costs as a function of age, annual utilization (miles traveled) as a function of age. Initial fleet configuration includes the numbers and ages of all vehicle types. Once all of the inputs are specified, the model can provide an optimal solution, together with cost breakdown and usage statistics.

A novel contribution of this work is to provide an optimization framework to fully analyze the sensitivity, elasticity and breakeven values of the key economic factors and technological characteristics of ECVs. The remainder of this paper is organized into five additional sections. Section 2 presents a literature review. Section 3 introduces the notation and formulation of the fleet replacement model and break-even analysis that is utilized to guide and optimize fleet replacement decisions. Section 4 describes data sources, assumptions, and evaluation scenarios. Section 5 presents and analyses the results of the optimization model as well as the elasticity and breakeven analysis. Section 6 ends with conclusions and discussion.

2. Literature review

The fast rate of commercial vehicle activity growth over the last decades and the higher impact of conventional commercial vehicles externalities (e.g. congestion, noise, and pollution) are resulting in stricter government regulation in dense urban areas. Additionally, social and political pressures to limit the impacts associated with carbon dioxide (CO_2) emissions and oil dependence are mounting rapidly. Light, medium and heavy trucks share 50% CO_2 emissions of all transportation modes and 13.8% CO_2 emissions of all sectors in the USA in 2009 (USEPA, 2011). Urban freight and commercial vehicles are also responsible for a large share of unhealthy air pollutants such as sulfur oxide, particulate matter, and nitrogen oxides (NOx) in urban areas (OECD, 2003). Even if commercial diesel vehicles have a 10% share of total urban vehicle-miles traveled, commercial diesel powered vehicles can account for up to 90% of NOx and particulate matter (PM) emissions (Bigazzi and Figliozzi, 2012). Also, commercial diesel vehicles are central to the oil dependence in the USA, because they share 35% (light, medium and heavy trucks) of USA total fuel consumption in all sectors in 2009 (Davis et al., 2011).

Industry reports indicate that battery technology is improving rapidly and the optimistic miles traveled by an ECV increase to a level of 100–150 miles (e.g. Navistar E-star and Smith Newton) with fully charged battery claimed by manufactories. In a recent interview with fleet managers such as Frito-Lay and FedEx, Martin (2011) found that the so-called range anxiety does not restrict fleet operators in practice. "Drivers of commercial delivery vehicles tend to follow the same route each day, so they have a pretty good idea how much power they will need. And since trucks typically return to the garage every night, there's little worry about finding a charger. Electrics are quiet, don't pollute, and vibrate less than diesels", says Mike O'Connell, director of fleet capability for Frito-Lay North America.

Due to their limited range, ECVs are restricted at the moment to urban areas. The average annual miles traveled by single unit trucks (more than 10,000 lbs. weight) are 12,382 miles and 14,380 miles in year 2008 (FHWA, 2010) and 2009 (FHWA, 2009), which are equivalent to 48 and 55 miles per weekday, or 34 and 39 miles per day. Also, according to a recent report by FedEx (Barnitt, 2011), the average daily miles traveled by delivery truck is 41.4 miles, which is significantly lower than the range achieved and publicized by ECVs manufacturers.

Since electric commercial vehicles are relatively new to the USA market, there is scant academic literature studying their competitiveness against conventional diesel trucks from a fleet operator's prospect. Davis and Figliozzi (forthcoming) developed a continuous approximation routing model to compare diesel trucks and ECVs technological and cost competitiveness under scenarios with different customer distributions and demands, and operating speeds. EC (2010) developed a simplified annual cost economic model to compare lifecycle costs between four vehicle technologies: internal combustion engine vehicles, hybrid electric vehicles, plug-in hybrid electric vehicles and electric vehicles. Costs analyzed include purchase cost, energy cost, maintenance cost, infrastructure cost, and vehicle and battery residual values. Several scenarios were evaluated to study the impact of government incentive and fleet annual utilization on the competitiveness among the four vehicle technologies. However, the model compare annual costs between different vehicle technologies each year between 2010 and 2030, vehicle optimal replacement cycles were not considered. Feng and Figliozzi (2011) presented a preliminary vehicle replacement model to analyze vehicle competitiveness.

Vehicle replacement models can be classified into two categories: research-oriented and practice-oriented. The latter are mostly simple heuristics. In practice-oriented models replacement decisions are usually made based on a set of criteria such as age, cumulative utilization, and maintenance cost thresholds. These are readily implemented heuristic models but suboptimal. A comprehensive review of practice-oriented models can be found in Kim et al. (2009). Research-oriented models seek to economically optimize fleet replacement decisions. The objective function is usually the minimization of total fleet costs over a given planning horizon. This paper extends an optimal fleet replacement model developed by Hartman (2000) to multiple vehicle technologies. The research-oriented literature can be broken into two kinds of models: homogeneous and heterogeneous models. In the former, the objective is to find the best policy in terms of replacement timing for a set of homogenous assets (Karabakal et al., 1994), in which replacement decisions for all individual assets are identical and therefore can be represented by one asset, dynamic programming approaches are usually used in these models; in heterogeneous models, vehicles are considered different (Hartman, 2000), in other words, different vehicles in one fleet may have different replacement decisions, and therefore, these types of models relax more constraints but are more difficult to solve, mixed integer programming approaches are usually used in these models. The optimization model used in this paper can deal with heterogeneous fleet vehicles. There is no research work that addresses the full competitiveness of commercial vehicles in terms of fleet replacement optimization though the competitiveness of electric passenger vehicles has been studied by Figliozzi et al. (2011), the timing of bus transit replacement decisions by Boudart and Figliozzi (2012), and the relatively competitiveness between hybrid and diesel buses has been studied by Feng and Figliozzi (2012).

The impacts of realistic commercial vehicle utilizations, battery cost replacement scenarios, and optimal replacement strategies on ECVs competitiveness have not been properly considered. Furthermore breakeven analysis mathematical formulations and results and presented in this research work.

3. Model formulation

This is a deterministic model. Future costs such as purchase prices, fuel price, salvage values, maintenance costs, fuel and electricity consumption rate and many other economic and technical factors are assumed to be known functions of time (age) and vehicle type. Given the uncertainty associated to some of the key input parameters (fuel prices, battery life and costs, etc.) a sensitivity analysis is later performed in Section 5.

Indexes:

- Type of truck/engine: $k \in \mathbf{K} = \{1, 2, , \ldots, K\}$,
- Age of a type k truck in years: $i \in \mathbf{A}_k = \{0, 1, 2, , \ldots, A_k\}$,
- Time periods, decisions are taken in each year: $j \in \mathbf{T} = \{0, 1, 2, , \ldots, T\}$.

Decision variables:

- X_{ijk} = the number of age-i, type-k trucks used in year j,
- Y_{ijk} = the number of age-i, type-k trucks salvaged at the end of year j,
- P_{jk} = the number of new type-k trucks purchased at the beginning of year j.

Parameters:

- A_k = maximum age of type k truck,
- u_{ik} = utilization (miles traveled per year) by an age-i, type-k truck (miles/year/vehicle),
- d_j = demand (miles need to be traveled by all vehicles) in year j (miles),
- b_j = budget (money available for purchasing new vehicles) in the beginning of year j ($),
- v_k = purchase cost of a type-k truck ($),
- s_{ik} = salvage revenue of an age$i$-, type-k truck ($), where $s_{0k} = v_k$,
- o_{ijk} = per-mile energy (diesel or electricity) cost of an age-i, type-k truck used in year j($/mile),
- m_{ik} = per-mile maintenance cost of an age-i, type-k truck ($/mile),
- e_{ik} = per-mile CO_2 emissions cost of an age-i, type-k truck($/mile),
- dr = discount rate, to account for the decreased value of money over time,
- h_{ik} = initial number of age-i, type-k trucks at the beginning of the time horizon (year 0),

Objective function:

$MinZ$

where the lifecycle costs are represented by Z.

$$Z = \sum_{j=0}^{T-1}\sum_{k=1}^{K} v_k \cdot P_{jk} \cdot (1+dr)^{-j} - \sum_{i=1}^{A_k}\sum_{j=0}^{T}\sum_{k=1}^{K} s_{ik} \cdot Y_{ijk} \cdot (1+dr)^{-j} + \sum_{i=0}^{A_k-1}\sum_{j=0}^{T-1}\sum_{k=1}^{K}[o_{ijk} + m_{ik} + e_{ik}] \cdot u_{ik} X_{ijk} \cdot (1+dr)^{-j} \tag{1}$$

Constraints:

$$\sum_{k=1}^{K} v_k \cdot P_{jk} \leqslant b_j \forall j \in \{0, 1, 2, \ldots, T-1\} \tag{2}$$

$$\sum_{i=0}^{A_k-1}\sum_{k=1}^{K} X_{ijk} \cdot u_{ik} \geqslant d_j \forall j \in \{0, 1, 2, \ldots, T-1\} \tag{3}$$

$$P_{0k} + h_{0k} = X_{00k} \forall k \in K \tag{4}$$

$$X_{i0k} + Y_{i0k} = h_{ik} \forall i \in \{1, 2, \ldots, A_k\} \forall k \in K \tag{5}$$

$$P_{jk} = X_{0jk} \forall j \in \{1, 2, \ldots, T\} \forall k \in K \tag{6}$$

$$X_{(i-1)(j-1)k} = X_{ijk} + Y_{ijk} \forall i \in \{1, 2, \ldots, A_k\} \forall j \in \{1, 2, \ldots, T\} \forall k \in K \tag{7}$$

$$X_{iTk} = 0 \forall i \in \{0, 1, 2, \ldots, A_k - 1\} \forall k \in K \tag{8}$$

$$X_{A_k jk} = 0 \forall j \in \{0, 1, 2, \ldots, T\} \forall k \in K \tag{9}$$

$$Y_{0jk} = 0 \forall j \in \{0, 1, 2, \ldots, T\} \forall k \in K \tag{10}$$

$$P_{jk}, X_{ijk}, Y_{ijk} \in I \in \{0, 1, 2, \ldots\} \tag{11}$$

The objective function, Eq. (1), minimizes the discounted sum of purchase, energy, maintenance, emissions costs and salvage revenue over the period of analysis, i.e. from year zero (present) to the end of year T. Purchase costs cannot exceed the yearly budget, Eq. (2). The total miles traveled by all used trucks should meet the yearly demand, Eq. (3). In the first year 0, the number of initial age-0 (new) trucks and the number of purchased age-0 trucks should be equal to the used age-0 trucks in year 0, Eq. (4). In the first year 0, the initial numbers of any types or any ages of trucks (other than age-0) should be either used or salvaged, Eq. (5). The purchased new trucks in all the other years should be equal to the number of used new trucks in each of those years, Eq. (6). The numbers of any used trucks in one year should be either used or salvaged in the next year, Eq. (7). It is assumed that all trucks will be sold in the last year of the planning horizon (T), Eq. (8). Any truck that reaches its maximal age will not be used anymore, Eq. (9). Any new purchased trucks cannot be sold immediately, Eq. (10). All decision variables must be non-negative integers, Eq. (11).

4. Data sources, initial assumptions, and scenarios

4.1. Data sources

This paper optimizes fleet replacement decisions in an environment where conventional diesel trucks (the incumbent) compete against electric commercial vehicles (the challenger). For a fair comparison, two truck types in the same category (size) are compared. The conventional diesel truck is one of the popular Isuzu N-Series; the challenger is the Navistar E-star; a new electric motor truck released in 2010. Table 1 contains key truck characteristics. Henceforward we assume that $k = 1$ for diesel trucks and $k = 2$ for electric vehicles. Hence, according to Table 1, $v_1 = \$50,000$, $v_2 = \$150,000$.

Ordering and delivery costs for purchasing new vehicles are assumed constant and equal for both vehicles and not considered in this study. The salvage or resale value depreciates with age and cumulative vehicle mileage. Since the real-world resale values are driven by specific market and vehicle conditions, there is no precise depreciation function for each vehicle

Table 1
Comparison of truck characteristics.

Truck types	Isuzu *N*-series $k = 1$	Navistar E-star $k = 2$
Maximum age	$A_1 = 15$	$A_2 = 15$
Purchase price ($)	$50,000[a]	$150,000[b]
Energy consumption	13.46[c] mpg	0.8[d] kW h/mile
Energy price	$3.95/gal[e]	$0.0983/kW h[f]
CO_2 emissions	8.92kg/gallon[g]	0.69kg/kW h[g]

[a] http://www.truckpaper.com/list/list.aspx?ETID=1&catid=27&Manu=ISUZU&Mdltxt=NPR+HD&mdlx=exact&bcatid=27/, average price for a 2011 Isuzu NPR truck.

[b] http://thesmartvan.com/blog/2011/02/08/4708/for-the-green-collar-white-van-man-navistars-new-estar-with-a-2-ton-payload/, February, 2011.

[c] http://www.fleetequipmentmag.com/Item/65345/seeing_is_believing.aspx, average Isuzu N-Series fuel economy tested in November, 2008.

[d] http://www.estar-ev.com/specs, February, 2012. The mpg_equivalent for Navistar E-star can be estimated by $3.95/gal/(0.8 kW h/mile * $0.0983/kW h) = 50.2 mpg_equivalent.

[e] http://www.eia.gov/petroleum/gasdiesel/, US Energy Information Administration, February, 2012.

[f] http://www.eia.gov/electricity/state/, electricity price for transportation sector, US Energy Information Administration, January, 2012.

[g] http://www.epa.gov/cleanenergy/energy-resources/refs.html, US Environmental Protection Agency, accessed in February 2012. The Isuzu N-Series CO_2 emissions is the average tailpipe emissions from a diesel truck, while the Navistar E-star CO_2 emissions is the average emissions from electricity generation process (0 tailpipe emissions).

type in the academic literature. EC (2010) provides a series of concave curves for vehicle depreciation value as a function of age at different annual utilization levels. These vehicle depreciation functions utilized in this research are shown as follows:

$$s_{ik} = (1-\theta_k)s_{(i-1)k} = v_k \cdot (1-\theta_k)^i, \quad \forall k \in K, \forall i \in \{1,\ldots,A_k-1\} \tag{13}$$

The depreciation rate is denoted by θ_k. it ranges between 15% and 25% when annual utilization is between 10,000 mile/year and 20,000 mile/year.

According to the vehicle energy consumption rates for the two trucks shown in Table 1, per-mile energy costs for the Isuzu and Navistar vehicles are calculated using Eqs. (14) and (15) respectively.

$$o_{ij1} = \frac{\$3.95/\text{gal} \times (1+fr)^j}{13.46\ \text{mpg}}, \quad \forall i \in \{0,1,\ldots,A_k-1\}, \quad \forall j \in \{0,1,\ldots,T\} \tag{14}$$

$$o_{ij2} = 0.8\ \text{kW h/mi} \times \$0.0983/\text{kW h} \times (1+er)^j, \forall i \in \{0,1,\ldots,A_k-1\}, \forall j \in \{0,1,\ldots,T\} \tag{15}$$

The annual fuel and electricity price inflation rates are denoted by fr and er respectively; they are assumed to be 3.5% and 1.8% according to the US Energy Information Agency forecast (EIA, 2012). Energy consumption rates are assumed to not vary with vehicle age.

According to the CO_2 emissions rate for the two trucks shown in Table 1, the per-mile CO_2 emissions costs are calculated using the following equation:

$$e_{i1} = \frac{8.92\ \text{kg/gal}}{13.46\ \text{mpg}} \cdot ec/1000, \quad \forall i \in \{0,1,\ldots,A_k-1\} \tag{16}$$

$$e_{i2} = 0.69\ \text{kg/kW h} \times 0.8\text{kW h/mi} \cdot ec/1000, \quad \forall i \in \{0,1,\ldots,A_k-1\} \tag{17}$$

The CO_2 emissions cost is denoted by ec ($/ton). Because there is no standard CO_2 emission or penalty cost, the impacts of CO_2 emissions are evaluated in the sensitivity analysis section.

We assume that maintenance costs increase with vehicle age and utilization. We utilize per-mile maintenance cost for light-duty diesel trucks provided by EC (2010). For electric trucks, there are no long-term maintenance cost statistics. However, electric motor trucks are much simpler in design and thus likely to be more economical to maintain and repair. In addition, electric vehicles do not require oil changes and have less moving parts. Based on existing data and projections, we assume that electric trucks are 50% less expensive to maintain than conventional diesel trucks according to EC (2010) and Motavalli (2010) – this assumption does not included battery costs which are analyzed in a later subsection.

$$m_{i1} = (0.2 + 0.04 \cdot i), \quad \forall i \in \{0,1,\ldots,A_k-1\} \tag{18}$$

$$m_{i2} = (0.1 + 0.02 \cdot i), \quad \forall i \in \{0,1,\ldots,A_k-1\} \tag{19}$$

4.2. Initial assumptions

As an initial condition, we assume that a fleet company owns at the time of analysis (year 0) 30 Isuzu trucks. To facilitative the understanding of replacement policies suggested by the model, the ages of the Isuzu trucks are uniformly distributed with two vehicles per age ranging from age 0 (two new vehicles) until age 14 (at least two vehicles must be retired at the end of year 0). The planning horizon is 30 years and the maximum vehicle ages are 15 years so that all the initial vehicles must be replaced sometime between year 0 and the end of year 14. Trucks are used between year 0 and year 29; all trucks are sold at market value at year 30. The discount rate is assumed to be 6.5% per year. The annual budget is assumed to be such that up to four electric trucks or twelve diesel trucks can be purchased each year.

4.3. Scenarios

Different fleets and companies may have very different demands (number of vehicles needed or miles have to be traveled) and operating environment. Conventional diesel trucks traveling in more hilly or congested routes tend to have lower fuel economy; electric trucks are less affected by congestion since the batteries can recharge with the braking energy and the engine shuts down and does not idle when the vehicle is stationary. Therefore, six scenarios are analyzed to study the impact of vehicle utilization and conventional diesel truck fuel efficiency on optimal replacement decisions; fuel efficiencies and utilization levels are summarized in Table 2.

The total annual demand (miles have to be traveled) is set at a level so that at least 30 trucks are required each year in each scenario. The high level of fuel efficiency is the average fuel efficiency of Isuzu *N*-series tested by the manufacturer and some companies (Brothers, 2008); the low fuel efficiency corresponds to the USA average of 8.5 mpg for single unit trucks (FHWA, 2010).

The average single unit truck utilization in the USA is 12,382 miles per year in 2008 (FHWA, 2010). Three annual utilization levels (12,000, 16,000 and 20,000 mile/year/truck) are tested to represent different levels of vehicle utilization within

Table 2
Scenarios.

Scenarios	Average annual utilization (mi/yr/truck)	Equivalent daily utilization (mi/weekday/truck)	Diesel truck fuel economy
S0	12,000 – Low	46	High 13.46 mpg
S1	16,000 – Mid	62	
S2	20,000 – High	77	
S3	12,000 – Low	46	Low 8.5 mpg
S4	16,000 – Mid	62	
S5	20,000 – High	77	

the range of the electric truck battery capacity, i.e. less than 100 miles per day without recharging. We denote these utilization levels Low, Medium, and High respectively. We assume not in-route recharging as the number of fast recharging stations is scant or null in urban areas across the USA.

The baseline scenario (S0) is meant to represent the toughest market conditions for the ECVs: a combination of relatively low utilization and high diesel truck fuel economy. Given the uncertainty and variability of some of the parameters, we also performed a comprehensive sensitivity and breakeven analysis to study the impact of each parameter on the competitiveness of ECVs and fleet per-mile discounted costs. Scenarios are denoted S0–S5 as shown in Table 2.

5. Results and sensitivity analysis

The optimal solutions are a joint function of economic and vehicular parameters. Results for each scenario are obtained utilizing a large scale mixed integer programming optimizer. This section is divided into four parts: (a) results regarding the impact of vehicle utilization and diesel fuel efficiency, (b) a breakeven analysis to understand when ECVs become competitive, (c) sensitivity analysis of parameters on fleet per-mile costs, and (d) a study of the impact of battery replacement costs on the competitiveness of ECVs.

5.1. Utilization and fuel economy scenarios

This subsection analyses the impacts of vehicle utilization and diesel truck fuel efficiency on fleet replacement decisions and fleet total cost breakdown. Table 3 summarizes the results of the six scenarios regarding vehicle usage.

- In the baseline scenario S0, ECVs are not purchased throughout the time horizon.
- ECVs clearly become more competitive to the end of the time horizon with higher utilization (S1 and S2) or low utilization level and low diesel truck fuel efficiency (S3); ECVs constitute almost 100% of the vehicles at the end of the time horizon and half of the total vehicles used throughout the time horizon.
- ECVs are clearly more competitive than conventional diesel trucks in medium or high utilization levels and low diesel engine fuel efficiency scenarios S4 and S5. In these scenarios, the optimal solutions suggest to replace 18 and 26 of the existing diesel trucks with new ECVs immediately (first year of the time horizon).
- Concluding, a medium or high utilization is needed to overcome the high initial capital cost of ECVs. ECVs will always be more appealing in routes or environments with low fuel efficiency for diesel engines.

A total fleet cost breakdown is shown in Fig. 1. In scenario S0, fuel costs and maintenance costs share the largest percentages of total discounted costs because there is no electric truck purchased throughout the time horizon; in scenarios S1, S2, and S3, the share of purchase costs increase while fuel cost percent share decreases due to the increasing adoption of electric trucks (50% throughout time horizon); in scenarios S4 and S5, the share of purchase costs increase significantly and fuel cost percent share decreases significantly because almost all vehicles used throughout the time horizon are electric trucks. CO_2

Table 3
Scenario results.

		S0	S1	S2	S3	S4	S5
Initial number of vehicles	Diesel	30	30	30	30	12	4
	Electric	0	0	0	0	18	26
Final number of vehicles	Diesel	30	2	0	2	0	0
	Electric	0	28	30	28	30	30
Average number of vehicles[a]	Diesel	30	15	15	15	0.6	0.2
	Electric	0	15	15	15	29.4	29.8

[a] Per year over the planning horizon.

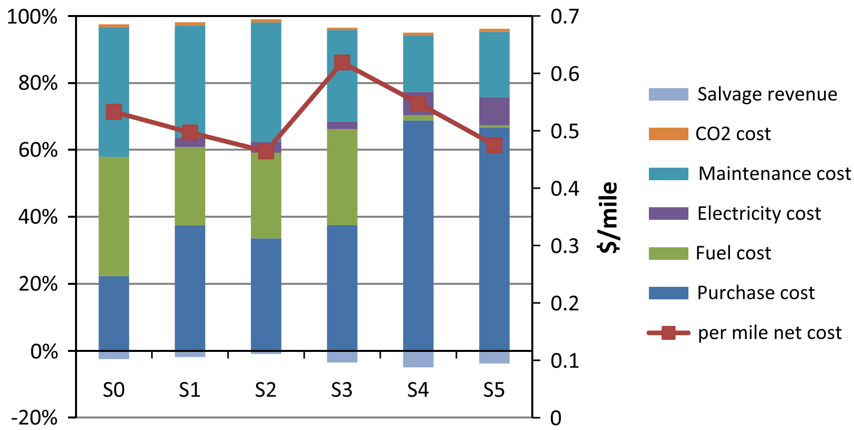

Fig. 1. Total cost breakdown and per-mile cost trends.

emissions cost and salvage revenues have very small shares of total discounted costs in all the analyzed scenarios. Per-mile discounted costs decrease with increasing annual utilization and increasing diesel truck fuel economy.

5.2. Breakeven analysis

Given the uncertainty and variability associated to some economic or technological parameters, we performed a breakeven analysis to understand under what conditions ECVs become competitive. We define the breakeven values as the value of a parameter, ceteris paribus, that leads to the purchase of at least one electric truck in year zero. For each scenario, breakeven values are found for 15 economic and technical factors as shown in Table 4.

The parameters are broken into factors that apply to:

- ***General Factors***, including the discount rate, utilization levels, carbon tax and planning time horizon.
- ***Electric Vehicle Factors***, including the ECV prices, depreciation rate, electricity price and inflation rate, ECV electricity efficiency, maintenance cost increasing slope, and maximum age. ECV prices are likely to go down when vehicles are mass produced or government incentives can be offered. The ECV depreciation rate and maintenance cost slope are uncertain factors since there is no historical data available for the new generation of electric trucks.
- ***Diesel Vehicle Factors***, such as diesel prices, diesel price inflation rate, and diesel truck fuel efficiency.

The results of the breakeven analysis are intuitive, see Table 4. ECV price has to decrease between 9% and 27% below the current market price to allow electric vehicles to become competitive in scenarios S0–S3. For example in scenario S0, the

Table 4
Breakeven analysis.

Factors ↓	Baseline values		S0	S1	S2	S3	S4	S5
General factors								
Discount rate: *dr*	6.5%	⩽	inf.[a]	2.3%	5.9%	3.9%	**8.6%**	**12.5%**
Annual utilization: u_{ik} (mi/year)	12 k, 16 k, 20 k	⩾	20,597	20,597	20,597	14,017	**14,017**	**14,017**
Daily utilization u_{ik} (mi/day)	46, 62, 77	⩾	79	79	79	54	**54**	**54**
CO_2 emissions cost: ($/ton)	0	⩾	3160	1093	158	973	**0**	**0**
Planning horizon *T*	30	⩾	inf.	inf.	inf.	inf.	**14**	**12**
Electric vehicle factors								
Electric truck price ($): v_2	150,000	⩽	110,239	128,637	147,150	136,472	**163,134**	**189,974**
Depreciation rate: θ_2	15%,20%,25%	⩽	2%	6%	17%	8%	**100%**	**100%**
Electricity price: ($/kW h)	0.0983	⩽	inf.	inf.	0.0824	inf.	**0.1919**	**0.326**
Electricity inflation rate: *er*	1.8%	⩽	inf.	inf.	inf.	inf.	**8.3%**	**15.9%**
Electricity efficiency: (kW h/mi)	0.8	⩽	inf.	inf.	0.668	inf.	**1.559**	**2.652**
Per-mile maintenance cost increasing slope: ($/mi/year)	0.02	⩽	inf.	inf.	0.016	inf.	**0.035**	**0.056**
Max age A_2	15	⩾	inf.	26	25	26	**14**	**14**
Diesel vehicle factors								
Diesel price: ($/gal)	3.95	⩾	7.45	5.38	4.11	4.70	**3.40**	**2.60**
Diesel price Inflation rate: *fr*	3.5%	⩾	16.5%	8%	4.1%	6%	**1.7%**	**0%**
Diesel fuel economy (mpg)	13.46, 8.5	⩽	7.15	9.86	12.98	7.15	**9.86**	**12.98**

[a] Inf. means there is no feasible value of the parameter that can make the electric truck to be purchased immediately at the beginning of time horizon (e.g. ⩽0 or ⩾+∞).

electric truck becomes competitive when the purchase price v_2 is less than \$110,239, which means the Navistar price should be reduced by 27% to become attractive enough to replace at least one existing Isuzu truck from the outset of the planning horizon. With medium or high utilization levels the price reductions needed are smaller: 14% and 9% for scenarios S1 and S2 respectively. In scenarios S4 and S5, the current electric truck price is smaller than the suggested breakeven price; this means that already at least one diesel truck has been replaced with electric truck in the first year of the time horizon (this is consistent with the results shown inTable 3). The breakeven values in Scenarios S0–S3 that seem more readily reached are shaded. The columns with bolded numbers show results where the ECVs are already competitive from the outset (S4 and S5).

Results from Table 4 also indicate that:

- Very low (almost unrealistic) discount rates are needed to make ECVs competitive in scenarios S0, S1, and S3, but only a moderate low discount rate (5.9%) is needed in scenario S2. On the other hand, only high discount rates (8.6% and 12.5%) can make ECVs not competitive in scenarios S4 and S5.
- ECVs can be competitive if their daily utilization is higher than 79 miles per day (over 20,597 miles per year) in high diesel fuel economy scenarios (S0–S2). Although it is uncertain whether the current battery technology can provide a range of 80 miles towards the end of the ECV life. This point is further analyzed in the battery replacement subsection.
- If CO_2 emissions costs are considered in fleet replacement decisions, ECVs should be more competitive. However, only extreme (unrealistic) high carbon taxes (in the range \$158–\$3160/ton) can have an impact on the competitiveness of ECVs even assuming that electric trucks generate no tailpipe CO_2 emissions (although we assume that there are some emissions associated to the production of batteries, see Table 1). As a reference, current carbon taxes in the European cap and trade system are around \$18 per ton of CO_2 (CarbonPoint, 2010).
- Extending the planning time horizon (even beyond 100 years) in the first scenarios (S0–S3) does not help ECVs to become competitive; however, ECVs are no longer competitive when the planning horizon is reduced to 14 or 12 years in scenarios S4 and S5 respectively. In other words, a fleet manager should not purchase ECVs when using planning horizons shorter than 12 years since the higher capital costs will not be recovered.
- The electricity prices, inflation rate, ECVs electricity efficiency, salvage depreciation rate and the per-mile maintenance cost slope that are needed to make the ECVs competitive are clearly infeasible or unrealistically low in scenarios S0, S1 and S3. On the other hand, they have to be unrealistic high to make ECVs not competitive in scenarios S4 and S5. Only in scenario S2 the competitiveness of ECVs is sensitive to realistic values of these factors.
- If ECVs are utilized until they are 25 or 26 years old, they can be competitive in scenarios S1, S2 and S3; while in scenario S0, even if ECVs can be used as long as the time horizon (30 years) without replacement they are not competitive; if ECVs are utilized less than 14 years old in scenarios S4 and S5 they are no longer competitive. Hence, maximum vehicle age has significant impact on the competitiveness of ECVs and this analysis assumes that the battery lasts for a period equal to the maximum life of the vehicle.
- Initial diesel fuel prices must increase to the \$4.1–\$4.7/gallon range to ensure the competitiveness of ECVs in scenarios S2 and S3. These numbers do not seem too unrealistic in the near future given the recent spike in oil prices. Alternatively, very high initial diesel prices and inflation rates are necessary to make ECVs competitive in scenarios S0 and S1. On the contrary, ECVs remain competitive in scenarios S4 and S5 even if initial diesel price and inflation rate are lower than current diesel prices.
- Comparing diesel prices with early 2012 European prices, \$6.7–8.8 per gallon, ECVs are already competitive in all scenarios. There is great variability in diesel prices across European countries with 1.3 Euros per liter of diesel in the Check Republic vs. 1.7 Euros per liter of diesel in Norway or the UK but in general Europe seems to provide competitive advantages for ECVs in terms of diesel prices.
- ECVs are competitive in environments where diesel trucks achieve fuel economies lower than 7.15 mpg, 9.86 mpg or 12.98 mpg in low, medium or high utilization scenarios respectively. These diesel truck fuel economy breakeven values are within realistic ranges especially in congested urban areas.

5.3. Elasticity analysis

In order to understand how each factor affects the fleet per-mile discounted cost, we compute the elasticity of fleet per-mile discounted cost with respect to each parameter employing the following arc elasticity formula (20) assuming a range shown in Table 5:

$$\eta_x^c = \frac{(x_1 + x_2)/2}{(c_1 + c_2)/2} \cdot \frac{\Delta_c}{\Delta_x} = \frac{(x_1 + x_2)}{(c_1 + c_2)} \cdot \frac{(c_2 - c_1)}{(x_2 - x_1)} \tag{20}$$

where η_x^c is the elasticity of per-mile discounted cost c to parameter x. For example for discount rate range between 40% and 9% the elasticity for scenario S0 is -0.64; this indicates that when the discount rate increases 1% the fleet per-mile discounted cost decreases 0.64%. Results with "0.00" elasticity indicates that the absolute value of the elasticity is less than 0.01.

Results from Table 5 show that discount rate and planning time horizon have the largest (absolute value) elasticity in all scenarios. Utilization and electric truck purchase cost have the largest elasticity in scenarios S4 and S5, indicating that in ECV dominated scenarios, utilization level and electric truck price have the highest positive impact on fleet per-mile discounted

Table 5
Per-mile discounted cost elasticity to all factors.

Factors	Baseline value	S0	S1	S2	S3	S4	S5
General factors							
Discount rate (4–9%)	6.5%	−0.64	−0.57	−0.52	−0.55	−0.43	−0.41
Low annual utilization (11,400–12,600 mi/yr)	12,000 mi/yr	−0.21			−0.37		
Median annual utilization (15,200–16,800 mi/yr)	16,000 mi/yr		−0.37			−0.70	
High annual utilization (19,000–21,000 mi/yr)	20,000 mi/yr			−0.37			−0.68
CO_2 emissions cost ($17–$19/ton)	$18/ton	0.00	0.00	0.00	0.00	0.00	0.00
Planning time horizon (28–32 years)	30 years	−0.52	−0.62	−0.57	−0.57	−0.77	−0.67
Electric vehicle factors							
Electric truck price ($142,500–$157,500)	$150,000	0.00	0.24	0.30	0.26	0.75	0.72
Low salvage depreciation rate (12–22%)	17%	0.00			0.02		
Median salvage depreciation rate (16–26%)	21%		0.01			0.04	
High salvage depreciation rate (20–30%)	25%			0.01			0.02
Electricity price ($0.0934–$0.1032/kW h)	$0.0983/kWh	0.00	0.03	0.03	0.02	0.08	0.09
Electricity price inflation (0–5%)	1.8%	0.00	0.01	0.02	0.01	0.03	0.03
Electricity efficiency (0.76–0.84 kW h/mi)	0.8 kWh/mi	0.00	0.03	0.03	0.02	0.08	0.09
Per-mile maintenance cost slope ($0.019–0.021/mi/yr)	$0.02/mi/yr	0.00	0.03	0.03	0.02	0.08	0.10
Max age (13–17 years)	15 years	0.00	−0.10	−0.13	−0.12	−0.20	−0.28
Diesel vehicle factors							
Diesel price ($3.75–4.15/gal)	$3.95/gal	0.38	0.24	0.24	0.31	0.02	0.01
Fuel inflation rate (0–5%)	3.5%	0.09	0.07	0.05	0.08	0.02	0.00
High diesel fuel economy (12.79–14.13 mpg)	13.46 mpg	−0.38	−0.24	−0.23			
Low diesel fuel economy (8.08–8.93 mpg)	8.5 mpg				−0.31	−0.02	−0.01

cost. On the other hand, utilization level, diesel price, and diesel truck fuel economy have the highest impacts in scenarios dominated by diesel trucks (S0). It noticeable that CO_2 emissions and the depreciation rate have the lowest elasticity values across all scenarios.

5.4. Battery replacement

The analyses in the previous subsections do not consider any battery replacement costs. However, due to the high battery costs and the uncertainty associated battery lives we analyze the effect of battery replacement on the competitiveness of ECVs. We incorporate battery replacement costs into the maintenance cost functions of electric trucks. According to EC (2010), electric vehicle battery should be replaced every 150,000 miles, therefore in this study, the battery replacement ages in low, medium and high utilization scenarios are 12, 9, and 7 years old respectively; EC (2010) also estimated that the battery cost in the next ten years will drop to approximately $400/kW h. After incorporating these battery replacement costs into the six scenarios, optimal replacement results are shown in Table 6.

Results from Table 6 indicate that after including battery replacement costs, the optimal replacement solutions in scenarios S1 and S4 changed significantly compared to results shown in Table 3. The average market share of ECVs throughout the time horizon drops from 50% to 0% in scenario S1 and from 98% to 50% in scenario S4. Also, ECVs are no longer purchased in year 01 in scenario S4. However, the average replacement age of ECVs remains 15 years in all scenarios where ECVs are used both before and after including the battery replacement cost in the middle of an electric truck's life cycle.

Breakeven values and elasticity results are shown in Tables 7 and 8. In Table 7, since only scenario S5 keeps ECVs competitive with a battery replacement, the shaded areas (values that are more readily reached) are mostly associated with this scenario and a few with scenario S4. For example, the utilization levels needed to breakeven in scenarios S0, S1, and S2 are clearly unreachable with current battery technology and ECV range.

Results from Table 8 show that the elasticity values do not change significantly (especially in scenarios S0 and S5 where the optimal replacement policies have not been altered). As in Table 5, we observe that: (a) discount rate and planning time horizon have the largest (absolute value) elasticity in all scenarios, (b) utilization and electric truck purchase cost have the

Table 6
Scenario results including battery replacement costs.

		S0	S1	S2	S3	S4	S5
Initial number of vehicles	Diesel	30	30	30	30	30	10
	Electric	0	0	0	0	0	20
Final number of vehicles	Diesel	30	30	0	2	4	0
	Electric	0	0	30	28	26	30
Average number of vehicles	Diesel	30	30	15	17.2	15	0.4
	Electric	0	0	15	12.8	15	29.6

Table 7
Breakeven values including battery replacement cost.

Factors ↓	Baseline values		S0	S1	S2	S3	S4	S5
General factors								
Discount rate: *dr*	6.5%	⩽	inf.	inf.	1.0%	inf.	4.4%	**9.8%**
Annual utilization: u_{ik} (mi/year)	12k, 16k, 20k	⩾	33,764	33,764	33,764	16,937	16,937	**16,937**
Daily utilization u_{ik} (mi/day)	46, 62, 77	⩾	130	130	130	65	65	**65**
CO_2 emissions cost: ($/ton)	0	⩾	4,472	2,149	1,033	2,949	294	**0**
Planning horizon *T*	30	⩾	inf.	inf.	inf.	inf.	inf.	**14**
Electric vehicle factors								
Electric truck price ($): v_2	150,000	⩽	99,515	110,245	126,432	118,416	144,741	**169,256**
Depreciation rate:θ_2	15%, 20%, 25%	⩽	2%	4%	7%	6%	14%	**100%**
Electricity price: ($/kWh)	0.0983	⩽	inf.	inf.	inf.	inf.	0.0617	**0.2062**
Electricity inflation rate: *er*	1.8%	⩽	inf.	inf.	inf.	inf.	inf.	**12.8%**
Electricity efficiency: (kWh/mi)	0.8	⩽	inf.	inf.	inf.	inf.	0.504	**1.675**
Per-mile maintenance cost increasing slope: ($/mi/year)	0.02	⩽	inf.	inf.	inf.	inf.	0.014	**0.038**
Max age A_2	15	⩾	inf.	inf.	inf.	29	26	**14**
Diesel vehicle factors								
Diesel price: ($/gal)	3.95	⩾	10.76	6.6	5.21	6.79	4.17	**3.3**
Diesel price Inflation rate: *fr*	3.5%	⩾	68.5%	19.1%	9.1%	25.8%	4.2%	**1.3%**
Diesel fuel economy (mpg)	13.46, 8.5	⩽	4.94	8.05	10.2	4.94	8.05	**10.2**

Table 8
Per-mile discounted cost elasticity after including battery replacement cost.

Factors	Baseline value	S0	S1	S2	S3	S4	S5
General factors							
Discount rate (4–9%)	6.5%	−0.65	−0.62	−0.58	−0.59	−0.54	−0.46
Low annual utilization (11,400–12,600 mi/yr)	12,000 mi/yr	−0.21			−0.25		
Median annual utilization (15,200–16,800 mi/yr)	16,000 mi/yr		−0.20			−0.34	
High annual utilization (19,000–21,000 mi/yr)	20,000 mi/yr			−0.35			−0.70
CO_2 emissions cost ($17–$19/ton)	$18/ton	0.00	0.00	0.00	0.00	0.00	0.00
Planning time horizon (28–32 years)	30 years	−0.52	−0.53	−0.61	−0.59	−0.57	−0.76
Electric vehicle factors							
Electric truck price ($142,500–$157,500)	$150,000	0.00	0.04	0.20	0.22	0.30	0.64
Low salvage depreciation rate (12–22%)	17%	0.00			0.03		
Median salvage depreciation rate (16–26%)	21%		0.00			0.02	
High salvage depreciation rate (20–30%)	25%			0.01			0.02
Electricity price ($0.0934–0.1032/kW h)	$0.0983/kWh	0.00	0.00	0.03	0.02	0.03	0.08
Electricity price inflation (0–5%)	1.8%	0.00	0.00	0.02	0.01	0.02	0.03
Electricity efficiency (0.76–0.84 kW h/mi)	0.8kWh/mi	0.00	0.00	0.03	0.02	0.03	0.08
Per-mile maintenance cost slope ($0.019–0.021/mi/yr)	$0.02/mi/yr	0.00	0.00	0.03	0.02	0.02	0.09
Max age (13–17 years)	15 years	0.00	−0.01	−0.05	−0.04	−0.16	−0.14
Diesel vehicle factors							
Diesel price ($3.75–$4.15/gal)	$3.95/gal	0.38	0.38	0.25	0.34	0.30	0.01
Fuel inflation rate (0–5%)	3.5%	0.10	0.08	0.07	0.09	0.06	0.02
High diesel fuel economy (12.79–14.13 mpg)	13.46 mpg	−0.38	−0.38	−0.25			
Low diesel fuel economy (8.08–8.93 mpg)	8.5 mpg				−0.34	−0.29	−0.01

largest elasticity in scenarios with higher ECV share, and (c) utilization level, diesel price, and diesel truck fuel economy have the highest impacts in scenarios dominated by diesel trucks. As in the previous analysis without battery replacement, CO_2 emissions and the depreciation rate have the lowest elasticity values across all scenarios.

The results indicate that a battery replacement clearly has a significant impact on the competitiveness between ECVs and diesel trucks and breakeven values in some scenarios. However, the impacts on elasticity values are more limited.

Looking towards the future, it is expected that improving battery technology will rapidly increase battery capacity (recently released electric commercial vehicle Smith Newton can travel 150 miles with fully charged battery) and decrease battery prices. These improvements will broaden the appeal of ECVs in the USA because currently they seem mostly viable in scenarios with either high utilization, high levels of governmental subsidies, or high diesel prices (e.g. at European levels).

6. Conclusions and discussion

This research is primarily focused on evaluating whether electric commercial vehicles, as a new challenger to conventional diesel trucks, are more cost effective than the conventional diesel counterparts. This research utilizes an optimal fleet replacement framework to find the key economic and technological factors that affect the competitiveness of electric commercial vehicles (ECVs). The presented methodology can be applied to any country or vehicle technologies though the results presented in this research represent 2011 figures for the USA market. The Isuzu N-Series and the Navistar E-Star were selected to represent diesel and electric trucks respectively.

Breakeven values and elasticity are calculated to analyze the impact of uncertain or hard to forecast economic or technological parameters on optimal replacement decisions and fleet per-mile discounted cost. The results clearly indicate that only in scenarios with high utilization (over 60 miles driven per day or 16,000 miles per year per truck) the electric vehicles are competitive. This is especially valid if a battery replacement is required before the electric commercial vehicle is replaced. The breakeven analysis results show that a 9% to 27% ECV price reduction can greatly increase their competitiveness when vehicles are driven over 12,000 miles per year even if diesel truck fuel economy is as high as 13.46 mpg. Planning time horizon, discount rate and annual utilization level are the three factors that significantly affect the fleet per-mile discounted cost in all scenarios. Electric truck price significantly affects the fleet per-mile discounted cost in ECV favorable scenarios, and diesel price and diesel truck fuel economy significantly affect the fleet per-mile discounted cost in diesel truck preferred scenarios.

Future research efforts can focus on a similar analysis in Europe or comparing other markets with significantly different purchase costs or diesel fuel prices. In addition, it is expected that ECVs costs and battery capabilities will change significantly in the near future and the presented results will have to be updated. However, it is important to highlight that the presented breakeven analysis is useful to provide an informative context for the findings. For example, in all cases if the fleet annual utilization is more than 22,000 miles per year per vehicle, ECVs become competitive assuming current USA market prices. Although 22,000 miles can be unrealistic with the present technology it may be readily achievable in the near future as battery technology improves and the results of this research are still relevant as long as other market values do not change significantly.

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