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Reducing transit fleet emissions through vehicle retrofits, replacements, and usage changes over multiple time periods

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ABSTRACT

Bus transit is often promoted as a green form of transportation, but surprisingly little research has been done on how to run transit systems in a green manner. Both vehicle task assignment and purchase models are generally constructed to minimize financial costs. Integrating vehicle task assignment with purchase decisions is made challenging by the different time scales involved. An integer programming approach is used to combine vehicle purchase, retrofit and aggregated task assignment decisions. The formulation is designed to operate in sequence with traditional vehicle task assignment models, to add emissions and long term financial cost elements to the objective, while maintaining computational tractability and feasible input data requirements. In a case study, a transit agency saves money in the long term by using stimulus money to buy CNG infrastructure instead of purchasing only new buses. Carbon prices up to \$400/(ton CO_2 equivalent) do not change vehicle purchase decisions, but higher carbon prices can cause more diesel hybrid purchases, at a high marginal cost. Although the motivation and numerical case study are from the US transit industry, the model is formulated to be widely applicable to green fleet management in multiple contexts.

1. Introduction

Bus transit is often promoted as a green form of transportation, but surprisingly little research has been done on how to run transit systems in a green manner. Research on transit vehicle assignment (the process of assigning vehicles to routes) focuses on minimizing capital and/or operating costs, or factors related to cost, such as the number of vehicles required. Even without including related problems such as driver scheduling, vehicle assignment problems can be very large and difficult to solve (Kliewer et al., 2006; Banihashemi and Haghani, 2000; Haghani et al., 2003). Li and Head (2009) stands out from other vehicle assignment research by including emissions constraints and penalties in its formulations. Unlike typical transit vehicle assignment models, they explicitly model vehicle purchases, limited by a capital budget.

Transit vehicle assignment models, including that of Li and Head (2009), are generally constructed to optimize the vehicle movements needed to cover all routes on a timetable, which is usually one day long. In transit, the timetables tend to repeat regularly (perhaps with variants depending on day of the week). It is a common practice to rework transit vehicle assignments several times per year, as adjustments to routes are introduced (Banihashemi and Haghani, 2000). Li and Head (2009) do not forecast how operational costs will change due to future route adjustments, or other factors such as shifting fuel prices. The impacts of current vehicle purchase and usage decisions on future capital expenditures are not considered. The fine grained nature of the time–space network, which is essential to short term vehicle assignment

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decisions, makes longer term planning difficult. As a result, vehicle purchase decisions are made with a very short planning horizon compared to the life of the vehicle. Simms et al. (1984) presented a long term model for planning the timing of bus purchases, as well as the degree to which buses are used in a given period. This model does not distinguish between different bus technologies, or between different duty cycles, and it does not include emissions objectives or constraints.

This paper proposes an integer programming method of making vehicle purchase decisions over a long time horizon, while simultaneously making vehicle task assignments at an aggregated level. The integer program minimizes operational costs, plus penalties for emissions, given capital budget constraints. Retrofits are incorporated as an alternate method of reducing emissions. Retrofits may only be compatible with some vehicles, and they may only be compatible with some tasks (depending on the exhaust temperatures generated). Gao and Stasko (2009) presented a model for developing retrofit and replacement strategies, but it only considered retrofits and replacements made at one point in time, and did not include the connected problem of vehicle task assignment.

Section 2 presents the integer programming methodology, while Section 3 describes a case study for a transit operator, and Section 4 outlines conclusions and potential extensions.

2. Model formulation

2.1. Expanding on traditional vehicle scheduling

Although the motivation and case study are from the transit industry, the model is formulated to be widely applicable to multiple types of fleets. The goal is to be able to model vehicle purchase, retrofit, and aggregated task assignment decisions over multiple periods, while considering both financial costs and emissions.

Perhaps the most straightforward way to lengthen the planning horizon of a traditional vehicle assignment model would be to include multiple connected networks. Each network could represent a typical day in a longer (perhaps quarterly) period. There are multiple reasons why such an approach would likely prove unreasonable, the most obvious being computational tractability. Solving a single time–space network problem for a decent sized transit system is already challenging, and multiple connected networks could easily be far worse. There is also a question of data availability. Exact timetables for the next few months are generally available, but it is extremely rare to know exactly how routes will change in the next decade.

The lack of detailed information about the future prompts consideration of a more aggregated approach. Budget constrained transit agencies might assign vehicles to routes to minimize the number of vehicles and drivers required, as well as operational expenses, before even considering emissions. The model presented in this paper assumes that such an assignment has already been made using traditional connection-based or time–space network approaches. The result is a set of assignment runs dictating what routes the bus assigned to that run will drive throughout the day. Each run requires one bus, and no bus may complete multiple runs. The next question is: how much flexibility remains in terms of which bus conducts which run, and how much is already dictated by the completed assignment?

It is conceivable that the vehicle assignment produced retains a fair amount of flexibility. The bus assignment may require that a single 40 ft. bus be used for a set of routes, but not necessarily which of such buses is used. There could be "swaps" of buses which are practically identical from an operational cost perspective, but quite different from an emissions perspective.

The degree of flexibility can be expanded if the costs associated with running a particular vehicle on a particular run (e.g. fuel and maintenance) are incorporated into the second stage optimization. Assignment swaps may increase operational costs, but only if other factors, such as emissions reductions, are worth the increase. Because the runs are kept intact, the general structure of the initial vehicle assignment will remain.

This sequential approach amounts to a decomposition, and there is the possibility that a truly optimal solution would involve changing which routes are included in which runs, based on emissions objectives. The fact that the details of future routes are unknown limits the likelihood that such a situation will seriously harm the quality of the solution produced. While it is difficult to predict the details of future routes, it may be much easier to predict the kind of daily runs which will exist (e.g. total mileage, the percentage of time spent on highways). For further simplification, assignment runs can be grouped, based on characteristics which impact costs and emissions, such as length and duty cycle, but this level of aggregation is optional. Groups can be of size 1.

The complete model formulation follows in Sections 2.2–2.7.

2.2. Sets

T	set of time periods
$R[t]$	set of assignment run groups for period t (including nonuse)
I	set of vehicle types in initial fleet
N	set of new vehicle types for possible purchase
J	set of retrofit options (including unretrofitted)
A	set of pollutants tracked

2.3. Input parameters

f_{ij}	# of vehicle type i with retrofit j in the initial fleet
l_i	expected remaining periods of use for vehicle type i at the start of period 1
λ_n	expected periods of usage for a new vehicle of type n
p_{nt}	cost to purchase vehicle type n at the start of period t
m_{tr}	# of buses required to cover assignment r in period t
c_{itr}	operating cost to cover assignment r with vehicle type i in period t
α_{ntr}	operating cost to cover assignment r with new vehicle type n in period t
v_{ijkt}	cost to switch vehicle type i from retrofit j to k at the start of period t
ξ_{ijtr}	1 if vehicle type i is compatible with retrofit j while covering assignment r in period t, 0 otherwise
e_{ijtra}	emissions of pollutant a for vehicle type i with retrofit j covering assignment r in period t
ε_{ntra}	emissions of pollutant a for new vehicle type n covering assignment r in period t
ω_a	unit "cost" of pollutant a
Φ_t	capital budget for period t
Ψ_t	retrofit budget for period t

2.4. Variables (all are non-negative)

x_{ijtr}	# of vehicles of type i with retrofit j covering assignment r in period t
y_{ijkt}	# of vehicles of type i switching from retrofit j to k at the start of period t
z_{ntr}	# of new vehicles of type n covering assignment r in period t
g_{ijt}	# of vehicles of type i with retrofit j retired at the start of period t
h_{nt}	# of new vehicles of type n retired at the start of period t
b_{nt}	# of new vehicles of type n bought at the start of period t
μ_t	amount by which capital costs exceed capital budget in period t

2.5. Constraints (apart from non-negativity of all variables)

$$\sum_{k\in J} y_{ijk1} = f_{ij} - g_{ij1} \quad \forall\ i \in I, j \in J \tag{1}$$

$$\sum_{k\in J} y_{ijkt} = \left(\sum_{r\in R[t-1]} x_{ij(t-1)r}\right) - g_{ijt} \quad \forall\ i \in I, j \in J, t \in T : t \neq 1 \tag{2}$$

$$\sum_{j\in J} y_{ijkt} = \sum_{r\in R[t]} x_{iktr} \quad \forall\ i \in I, k \in J, t \in T \tag{3}$$

$$\sum_{r\in R[1]} z_{n1r} = b_{n1} - h_{n1} \quad \forall\ n \in N \tag{4}$$

$$\sum_{r\in R[t]} z_{ntr} = \left(\sum_{r\in R[t-1]} z_{n(t-1)r}\right) + b_{nt} - h_{nt} \quad \forall\ n \in N, t \in T : t \neq 1 \tag{5}$$

$$\sum_{j\in J} f_{ij} = \sum_{j\in J} g_{ij(l_i+1)} \quad \forall\ i \in I \tag{6}$$

$$h_{nt} = b_{n(t-\lambda_n)} \quad \forall \in N, t \in T : t > \lambda_n \tag{7}$$

$$\left(\sum_{i\in I} \sum_{j\in J} x_{ijtr}\right) + \left(\sum_{n\in N} z_{ntr}\right) \geqslant m_{tr} \quad \forall\ t \in T, r \in R[t] \tag{8}$$

$$\xi_{ijtr} \sum_{k\in J} f_{ik} \geqslant x_{ijtr} \quad \forall\ i \in I, j \in J, t \in T, r \in R[t] \tag{9}$$

$$\sum_{n\in N} b_{nt} p_{nt} \leqslant \Phi_t + \left(\Psi_t - \sum_{i\in I} \sum_{j\in J} \sum_{k\in K} y_{ijkt} v_{ijkt}\right) \quad \forall\ t \in T \tag{10}$$

$$\sum_{i\in J}\sum_{j\in J}\sum_{k\in K} y_{ijkt}\, v_{ijkt} \leqslant \Psi_t \quad \forall\, t \in T \tag{11}$$

$$\left(\sum_{n\in N} b_{nt} p_{nt}\right) - \Phi_t \leqslant \mu_t \quad \forall\, t \in T \tag{12}$$

Expressions (1)–(3) are conservation of flow constraints for vehicles in the initial fleet, while expressions (4) and (5) are conservation of flow constraints for new vehicles. Expressions (6) and (7) require that initial and new vehicles (respectively) be retired at their expected retirement age if they reach it within the scope of the model. Expression (8) ensures that each assignment is met by the required number of vehicles. Expression (9) disallows retrofits from being used on vehicles and assignments with which they are incompatible.

Expression (10) enforces the capital budget constraint for each period. There is assumed to be some amount of money (possibly zero) which the fleet owner is willing to spend out of operational expenses in each period to fund emission reduction retrofits and speed up or upgrade vehicle replacements. Expression (11) ensures that while this money can supplement the normal capital budget, the capital budget cannot be used for retrofits. Expression (12) forces μ_t to be greater than or equal to the amount by which capital costs exceed the capital budget, while its non-negativity forces it to be greater than or equal to 0 in the case that capital costs are less than the capital budget. The inclusion of μ_t in the objective in expression (13) will push it to as low a value as constraints allow.

2.6. Objective

Minimize:

$$\sum_{t\in T}\left[\sum_{i\in I}\sum_{j\in J}\left(\left(\sum_{k\in K} y_{ijkt}\, v_{ijkt}\right)+\left(\sum_{r\in R[t]} x_{ijtr} c_{itr}\right)\right)+\mu_t+\sum_{n\in N}\sum_{r\in R[t]} z_{ntr}\alpha_{ntr}+\sum_{i\in I}\sum_{j\in J}\sum_{r\in R[t]}\sum_{a\in A}\omega_a e_{ijtra} x_{ijtr} \right.$$
$$\left. +\sum_{n\in N}\sum_{r\in R[t]}\sum_{a\in A}\omega_a z_{ntr}\varepsilon_{ntra}\right] \tag{13}$$

The objective, given by expression (13), is to minimize the combination of operational costs (including those falling under the retrofit budget used for retrofits or replacements) and penalties for emissions produced.

2.7. Depot modifications

Some potential new vehicle types, such as compressed natural gas (CNG) buses, might require a facility upgrade in order to operate. This can be incorporated by adding a parameter γ_t for the cost to implement the facility upgrade at the start of period t, and a variable β_t, which is 1 if a facility upgrade is made at the start of period t, and 0 otherwise. Let Ω be the set of new vehicles which require the depot modification and θ be a sufficiently large number (larger than the most buses which would ever be purchased in a single period). Expression (14) then requires the depot modification be in place for these vehicles to be purchased. It is straightforward to incorporate this cost into capital budget constraints in expressions (10) and (12).

$$\sum_{s\in 1..t} \theta\beta_s \geqslant b_{nt} \quad \forall\, n \in \Omega, t \in T \tag{14}$$

3. Case study and data sources

3.1. Available vehicles, assignments, and retrofits

The case study represents a modest sized public transit system in the US. The initial fleet is composed of four conventional diesel buses from each model year 1997–2004, three conventional diesels from 2005, three diesel hybrids from 2006 and 2007, and three conventional diesels from 2008. All of the initial fleet is unretrofitted. Both conventional and hybrid diesel buses are available for purchase, as are CNG buses (provided the necessary depot modifications are made in the same period or earlier). All vehicles are assumed to have a lifespan of 15 years, based on a review of the FTA's extensive National Transit Database (Laver et al., 2007).

Each assignment run can contain periods on a central business district (CBD) driving cycle as well as the Orange County Transit Agency (OCTA) cycle. The first assignment group requires 15 vehicles and is 75% CBD, while the second requires 15 vehicles and is 25% CBD, and the third requires 14 vehicles and is 50% CBD. All runs are assumed to include 37,000 miles/year of driving, the average annual mileage of a transit bus (Laver et al., 2007).

Three retrofit options are available: diesel oxidation catalysts (DOCs), passive diesel particulate filters (PDPFs), and active diesel particulate filters (ADPFs). Retrofit costs are \$1280, \$8160, and \$16,320 for DOCs, PDPFs, and ADPFs respectively.

Retrofits are only compatible with pre-2007 model year diesel vehicles. A DOC is a catalyzed portion of the exhaust system. Exhaust temperature requirements are relatively low, making DOCs compatible with all assignments. PDPFs are generally catalyzed portions of the exhaust system like DOCs, but they also have a physical filter. The physical filter can stop a much larger fraction of the particulate mass, but it comes with the challenge of disposing of everything it collects. Regenerating filters burn off the trapped particulates, but they can be sensitive to temperature. If temperatures are too low to support regeneration for a long period, the buildup can burn at too high a temperature when finally ignited, causing damaging temperature gradients (van Setten et al., 2001). PDPFs are considered incompatible with the high amount of "stop and go" in the 75% CBD assignment group. ADPFs address the temperature problem by providing additional heat for regeneration. This makes them compatible with all assignments, but they come at a substantially higher cost than other retrofits.

3.2. Cost and budget parameters

Vehicle purchase costs, given in Table 1, are adjusted versions of those in Clark et al. (2007). For CNG vehicles, depot modification and fueling station installation costs are taken from Clark et al. (2007). Hybrids and conventional diesels require no facility changes. Lifetime maintenance costs in Clark et al. (2007) were converted to a per mile basis. These maintenance costs, given in Table 1, include battery replacement for hybrids and compression electricity for natural gas. All vehicle and maintenance costs are expected to rise at the rate of discount.

Table 1
Vehicle fuel efficiencies and costs.

	Conventional diesel	Diesel hybrid	CNG
CBD fuel economy (mpg[a])	4.1	5.17	3.75
OCTA fuel economy (mpg[a])	4.14	4.9	3.52
Maintenance cost/mile	$0.20	$0.33	$0.24
New vehicle purchase price	$321,143	$531,605	$342,366
Depot modification and refueling station cost	$0	$0	$2875,000

[a] For CNG, miles per diesel gallon equivalent.

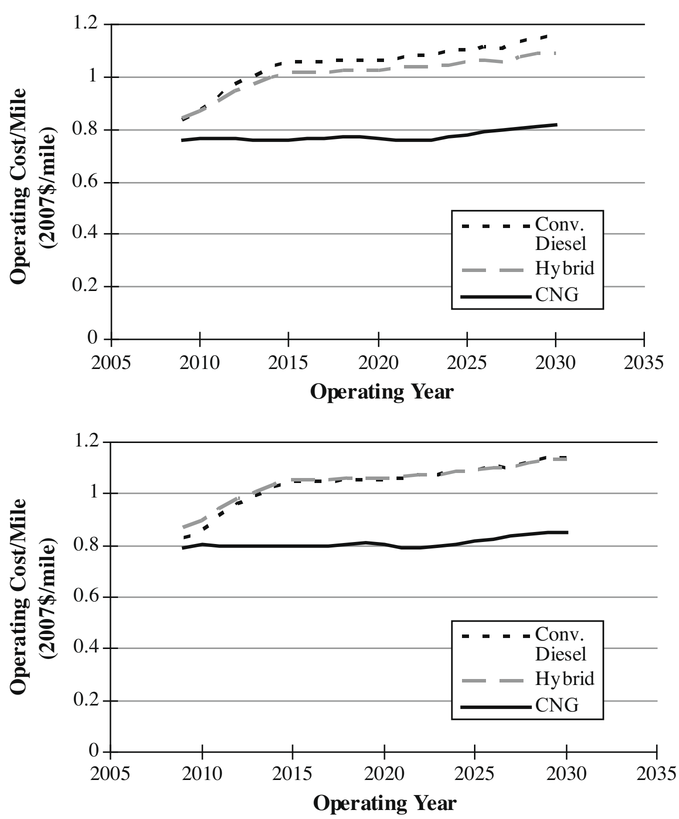

Fig. 1. Operating cost per mile (fuel and maintenance) for CBD duty cycle (top) and OCTA duty cycle (bottom).

Current and future fuel prices are taken from the US Department of Energy's Annual Energy Outlook (US DOE, 2009a). Transit bus fuel efficiencies for CBD and OCTA driving cycles reported are from Clark et al. (2007). Fig. 1 shows operating costs per mile (fuel and maintenance) for CBD and OCTA cycles, in the top and bottom graphs respectively. A few calculations reveal that for the hybrid's higher maintenance cost to be offset by its fuel efficiency requires a fuel price of $2.74 for the CBD cycle and $3.69 for the OCTA cycle.

The transit agency is assumed to have a capital budget just large enough for four new conventional diesel vehicles per year. In addition, they are receiving $2.5 million in stimulus money which must be spent at the start of 2010. The annual retrofit budget is $50,000.

3.3. Emissions rates

Each vehicle type and driving cycle has an associated greenhouse gas emission rate, based on Clark et al. (2007). All greenhouse gas emission rates are "well-to-wheel" rates, meaning they include the entire process of producing, refining, transporting, and finally using the fuel. Tailpipe greenhouse gas emissions include CO_2 and CH_4. Clark et al. (2007) drew their non-tailpipe emission rates from the Department of Energy's GREET model, which includes CH_4 and N_2O as well as CO_2 (Argonne National Laboratory, 2007).

Apart from greenhouse gases, diesel emission rates are from the EPA's MOBILE6.2 model. Separate emission rates were produced for the CBD and OCTA cycles. MOBILE does not produce separate emissions rates for hybrid diesel buses, so the same $PM_{2.5}$, nonmethane hydrocarbon (NMHC), and NO_x rates were used. Holmén et al. (2005) found that hybrid bus particulate emissions matched those from a conventional diesel bus using comparable emission control technology. Foyt (2005) found very similar particulate matter, NO_x and HC emission rates for hybrids and conventional diesel buses.

Clark et al. (2007) was used in place of MOBILE for CNG emission rates. The MOBILE User Guide admits its post-2003 CNG emission factors are probably not realistic and recommends finding alternate CNG factors (US EPA, 2003). Clark et al. (2007) provides model year 2007 CNG emission rates for both driving cycles. CNG emission rates are assumed not to change post-2007.

The emissions reductions from retrofits are based on typical retrofits verified by the US EPA (2009). DOCs are assumed to reduce $PM_{2.5}$ by 40%, and NMHC by 70%, while both PDPFs and ADPFs are assumed to reduce $PM_{2.5}$ by 90% and NMHC by 85%.

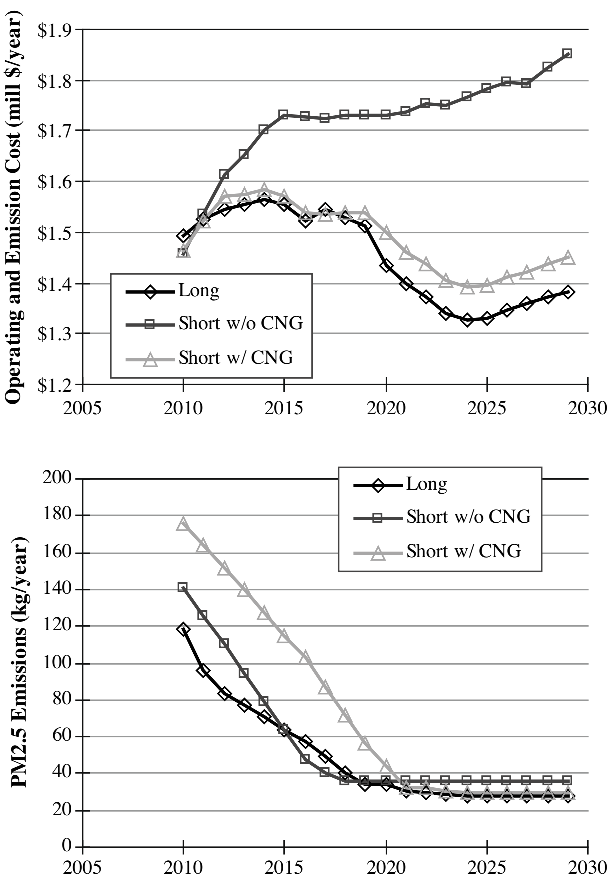

Fig. 2. Operational costs and emission penalties over time (top) $PM_{2.5}$ emissions over time (bottom).

When a penalty for $PM_{2.5}$ emissions was added to the objective function, the $PM_{2.5}$ emissions were valued at $0.35/gram, based on guidelines for cost effectiveness of projects funded by CARB's Carl Moyer Program (CARB, 2009). Unless otherwise noted, no penalty was imposed for other emissions.

3.4. Comparison of long and short horizon model results

It is natural to ask how decisions made by a long horizon model compare to those made by a sequence of short horizon models. Does the capability of the model presented in this paper to simultaneously consider retrofit/replacement actions in multiple time periods have any benefits? Does decomposition into a series of single period models produce the same results? In order to answer these questions, the presented model was first run for 20 years simultaneously, and then a single period version was run 20 times in sequence. Retrofit and replacement decisions made using a one year horizon can indeed have significantly higher costs and emissions than those made using a 20 year horizon.

The operational costs plus $PM_{2.5}$ penalties are plotted for each year in Fig. 2 (top), while the $PM_{2.5}$ emissions for each year are plotted in Fig. 2 (bottom). The lines marked "long" are those from the long horizon model, while those marked "short w/o CNG" are those from the short horizon model. It is evident from the purchase decisions in Fig. 3 (top and middle) that one of the biggest differences between the long and short horizon decisions was that the long horizon model chose to use the stimulus money to buy CNG depot modifications, allowing it to convert much of the fleet to CNG over time. The long term fuel cost savings was not apparent to the short horizon model for period 1, so it chose to buy 11 conventional diesel buses instead. The line marked "short w/ CNG" is the short horizon model run independently for each of the 20 years, but with the mandate that it purchase CNG depot modifications in the first period when it has stimulus funds. The purpose of this extra case is to determine to what extent the conversion to CNG is responsible for the cost and emissions discrepancies between the long and short horizon models.

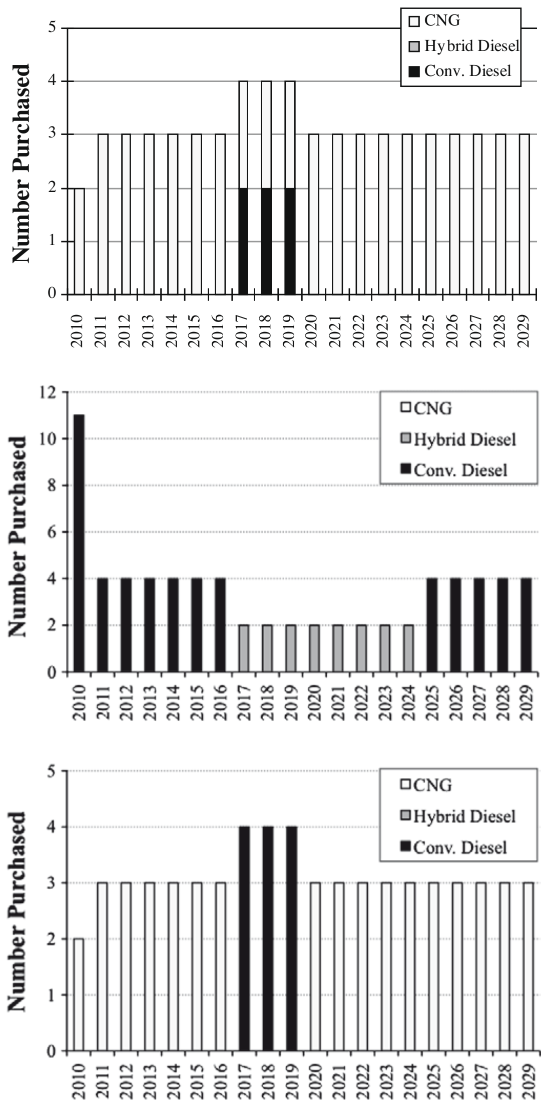

Fig. 3. Vehicle purchase for (top) long horizon model (middle) short horizon model (w/o CNG Mandate) (bottom) short horizon (w/o CNG Mandate).

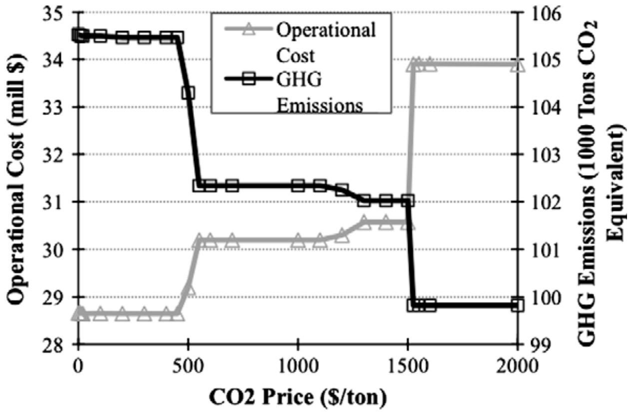

Fig. 4. Operational costs and greenhouse gas emissions as a function of carbon price.

In the first period, the long horizon model has the worst objective value, but by the second period it has pulled ahead of the short horizon model without the CNG mandate, and by the third period it is ahead of the short horizon model with the CNG mandate. The gap between the long horizon model and the short horizon model without the CNG mandate grows dramatically, reaching nearly half a million dollars in the last year. This is largely, but not entirely, due to the increasing gap in fuel cost between CNG and diesel vehicles.

Even given the CNG mandate, the short horizon model makes vehicle purchases which end up costing more in the long term. With or without the CNG mandate, the short horizon model fails to see the long term cost effectiveness of diesel retrofits, and does not conduct any. The long horizon model installs both DOCs and PDPFs in the first two periods, resulting in its initially low $PM_{2.5}$ emissions. The emissions gap decreases over time as replacements lower emissions across the board. The financial portion of the objective is far larger than the $PM_{2.5}$ penalty, always accounting for more than 95% of the objective value.

Another noteworthy aspect of the short horizon model is its propensity to put itself into infeasible situations. The example case study was constructed with relatively regular retirements, with enough of a budget in each year to cover the needed new buses. Several other case studies revealed that the greater the degree to which retirements are irregular, the more likely the short horizon model is likely to purchase too few vehicles early on, causing an infeasible problem later.

Both the long and short horizon integer programs were solved with CPLEX11.2.1. The largest instances had on the order of 10,000 variables, and converged in less than 30 s.

3.5. Impact of carbon pricing

In order to evaluate how potential carbon prices could influence behavior, the long horizon model was run with a range of penalties on greenhouse gases (expressed in dollars per ton of CO_2 equivalents). The resulting operational cost (not including emission penalties) and greenhouse gas emissions are plotted in Fig. 4. Up through penalties of $400/ton, the vehicle purchases match those in Section 3.4, with different retrofits and assignments, resulting in greenhouse gas emissions savings of less than 0.1%. Higher penalties, up through $1500/ton, cause hybrid purchases to replace CNG purchases, but CNG buses remain the most common purchase. Penalties of $1550/ton and greater cause the CNG refueling station to no longer be worth the investment, and all purchases are either conventional or hybrid diesel.

The greenhouse gas penalties required to make the switch from CNG buses to hybrids are quite high. Assuming projected 2020 fuel prices and a 50% CBD duty cycle, switching from a CNG bus to a hybrid costs roughly $500/ton of CO_2 equivalent reduced, in terms of operational costs only. Depending on when the bus is purchased, and what assignments it drives, this cost varies somewhat. This variation is accounted for in the integer program, and is part of why bus purchases are swapped gradually over a range of penalty levels. The high capital cost of hybrid buses also plays a role, by eliminating the possibility of completely switching to hybrids. Elimination of CNG purchases leads to more purchases of hybrids, which lower greenhouse gas emissions, but it also leads to more purchases of conventional diesels, with higher greenhouse gas emissions.

As a basis for comparison, estimates of the cost of carbon sequestration are often in the range of 30–100 $/ton (Davison, 2007; US DOE, 2009b; Creyts et al., 2007), depending on the type of plant involved, among other factors. McKinsey's 2007 report on reducing US greenhouse gas emissions includes a long list of methods which are estimated to cost under $50/ton of CO_2 equivalents (Creyts et al., 2007).

4. Conclusions

This research presents an integer program to be used in sequence with traditional vehicle task assignment algorithms. It allows for aggregated vehicle task assignment changes while developing a vehicle purchase and retrofit strategy for multiple periods in time. It can be effectively applied over a longer horizon than a traditional transit vehicle task assignment model incorporating vehicle purchases. A realistic case study revealed that a short horizon model applied iteratively yielded vehicle purchase and retrofit decisions which resulted in higher costs and emissions than the long horizon model presented in this paper.

The current model formulation converged quickly for the case studies performed. For the case study presented, CNG emerged as a key technology, both for cost and emission reduction. Hybrids did offer lower greenhouse gas emissions, but at very high marginal cost compared to CNG buses. This result was highly influenced by fuel price predictions made by the Department of Energy. Future research might incorporate uncertainty surrounding these predictions. Other sources of uncertainty, such as vehicle prices, budget fluctuations, and vehicle lifetimes could also be considered.

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