Trading off costs, environmental impact, and levels of service in the optimal design of transit bus fleets

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ABSTRACT

The development of a systematic framework to support the design of transit bus fleets is justified by the significant and long-lasting implications associated with decisions to purchase transit vehicles, as well as by developments in fuel propulsion and battery technologies over the last 2 decades that have increased the options available to transit operators, and, in turn, the complexity of assessing the corresponding tradeoffs. The need to evaluate these tradeoffs is, in part, driven by the emergence of environmental impact mitigation, i.e., emissions reductions, as a critical concern of transit operators and governments around the world.

To address these concerns, we present an optimization model to support the design of transit bus fleets while accounting for costs, level-of-service requirements, and environmental impact. Methodologically, the work bridges applications of Economic Input-Output analysis to conduct environmental lifecycle assessment, with seminal work in production economics.

We apply the framework to support design of bus fleets consisting of 4 bus types differing in their fuel-propulsion technology: ultra-low sulfur diesel, hybrid diesel-electric, compressed natural gas, and hydrogen fuel-cell. The 4 bus types were assessed in the National Renewable Energy Laboratory transit bus evaluation and demonstration studies conducted over the period 2003–2009. The nominal problem herein is to minimize acquisition, operation and disposal costs. Constraints in the model are used to impose a minimum frequency of service, i.e., headway, and to ensure that route capacity satisfies passenger demand. Environmental impact is considered along the following dimensions: energy consumption, and emissions of greenhouse gases, particulate matter, and nitrous oxides. Results show that fleet heterogeneity increases in scenarios where demand fluctuates, i.e., peak vs. off-peak. Perhaps even more interesting, we show how the dual/shadow prices provide a (monetary) measure of the tradeoffs among level of service and environmental impact, and discuss how they can be used to obtain robust fleet configurations.

1. Introduction

The decision to purchase transit vehicles has long-lasting implications for the lifecycle costs, emissions, and level of service provided by a transit agency. Perhaps, because the variety of buses is relatively low, and because of the increased complexity of managing heterogeneous fleets, the literature on bus fleeting is not extensive. However, as technology has developed, buses have grown increasingly heterogeneous in a variety of important metrics, including capacity, price, and operating characteristics. Recent and projected advances in alternative fuel and battery technologies have added an interesting dimension that will be relevant for the
foreseeable future. The practical motivation for our work, therefore, related to the complexity of decisions facing agencies in terms of assessing the relevant tradeoffs.

Methodologically, the work builds on Croft McKenzie and Durango-Cohen (2010), and bridges applications of Input-Output (IO) analysis to conduct environmental lifecycle assessment (LCA), with seminal work in production economics. In the latter, product design, production planning and scheduling problems are frequently formulated as IO models with substitution, and subsequently analyzed and solved as linear programs (cf. Shephard, 1953; Hackman and Leachman, 1989). Indeed, and as described in Koopmans (1951), these types of problems are among the first applications of linear programming. In addition to providing decision-support, the framework provides a well-established approach to conduct sensitivity analysis, i.e., to evaluate the effect of perturbations in the inputs on the results.

We apply the framework to support design of bus fleets consisting of 4 bus types differing in their fuel-propulsion technology: ultra-low sulfur diesel, hybrid diesel-electric, compressed natural gas, and hydrogen fuel-cell. The 4 bus types were assessed in the National Renewable Energy Laboratory transit bus evaluation and demonstration studies conducted over the period 2003–2009. Data are also from the environmental LCA in Croft McKenzie and Durango-Cohen (2012). The nominal problem herein is to minimize acquisition, operation and disposal costs. Constraints in the model are used to impose a minimum frequency of service/maximum headway, and to ensure that capacity satisfies passenger demand. Environmental impact is considered along multiple dimensions. Results show that fleet heterogeneity increases in scenarios where demand fluctuates, i.e., peak vs. off-peak. Perhaps even more interesting, we show how the dual/shadow prices provide a (monetary) measure of the tradeoffs among level of service and environmental impact, and discuss how they can be used to obtain robust fleet configurations.

The remainder of the paper is organized as follows. In the next section, we provide a brief review of the relevant literature. A formulation capturing the tradeoffs in designing bus fleets is presented in Section 3. Data used in the present study are presented in Section 4. In Section 5, we consider a number of scenarios where the optimization model is used to select bus fleets. Discussion of the results and conclusions of the study are presented in Section 6.

2. Background

Two streams of literature are related to the work presented herein. On the one hand, planning models aimed at capturing the tradeoffs between costs and level-of-service, i.e., capacity and frequency/headway; and on the other hand, environmental LCAs of transit vehicles.

In planning models, decisions to purchase a given type and number of buses are usually subordinated to routing and scheduling problems. That is, the number of buses to satisfy demand is derived for a given level of service and bus route/schedule, and under the assumption of homogenous bus type/technology. Hauer (1971) and Navin (1979) are pioneering studies. Vuchic (2005) is, perhaps, first to examine heterogeneity in bus capacity: either high or low capacity, with corresponding price and operating cost differences. In addition to costs, tradeoffs between the buses are explored along the following dimensions for peak and off-peak service: frequency/headway, passenger wait and load factors. Hsu and Wu (2008) builds on the aforementioned models and proposes a fleet size model for number of cars per train or BRT platoon. Other approaches to support bus fleet design include Khasnabie et al. (2003) and Peet et al. (2009). The former studies optimal replacement schedules to meet long-term fleet needs. The latter proposes a tool to allow transit operators to explore the tradeoffs between different bus technologies.

Environmental LCA of transportation and transit vehicles is an ongoing field of research. Chester and Horvath (2009) has compiled what is, perhaps, the most comprehensive look at transit vehicles to date. Another substantial evaluation of previous LCAs is presented in MacLean and Lave (2003). However, research that accounts for the operating characteristics of alternative fuel vehicles is still in its early stages, in part, because deployment of such vehicles is not widespread, and thus, (field) data are not widely available. Most studies on alternative fuel vehicles have focused on automobiles and on tailpipe emissions. Findings on alternative fuels in transit vehicles are mixed. In one of the first studies to relate environmental and economic costs, Johansson (1999) used lifecycle emissions calculations to look at economic efficiency. He found that CNG buses can result in fuel savings of up to 35%. Hess (2007) reports that, although purchase price gaps were declining between CNG and diesel buses, higher labor and maintenance costs are still significant. In a review of GHG-tailpipe emission and vehicle LCAs, Hesterberg et al. (2009) concluded that these mixed results are, in part, attributable to the complexity and uncertainty involved in measuring the lifecycle emissions associated with a vehicle.

Various approaches have been used to conduct the LCAs, with economic IO models, labeled EIO-LCAs, constituting an appealing one (Hendrickson et al., 2006). Rather than mapping processes in detail, e.g., chemical reactions, the IO approach involves specifying the requirements or bill of materials of a product in terms of demand for economic sectors such as transportation, construction, or financial services. The model, in turn, is used to compute the economic activity and environmental repercussions associated with satisfying the given demand for the product. Because all sectors represented in the economy are linked, there is no effective boundary on the scope of the analysis. The number and diversity of EIO-LCAs has greatly increased since the late 1990s as a result of the methodology’s flexibility, simplicity, and, importantly, the availability of tools and models to support the analysis. Examples can be found in the fields of waste disposal (Kondo and Nakamura, 2004), transportation (Facanha and Horvath, 2007), and service industries (Hendrickson et al., 2006). Although they have provided much insight, EIO-LCAs have been used almost exclusively as descriptive tools. That is, EIO-LCA models have not been integrated into a prescriptive framework to support decisions that arise during product/process design or (production) planning. To address this limitation, we build on the model of Croft McKenzie and Durango-Cohen (2010), and use it to address the problem of designing bus fleets.
3. Bus fleeting problem

We begin this section by describing the fundamental level-of-service tradeoffs inherent in the selection of transit buses. We then formulate the fleeting problem as a linear program.

3.1. Tradeoffs between frequency and capacity

The fleeting problem consists of determining the number of buses needed to meet passenger demand at a predetermined level of service. The parameters of the problem fall under the categories of demand, level of service, bus capacity, costs, and environmental impact. Demand corresponds to the number of passengers that needs to be served. Capacity is the ability of each bus to serve demand. Level of service is decided by a policy to run buses at certain intervals, which in turn determines the (average/maximum) time that passengers wait. Cost represents the cost to the transit operator to own and operate buses. Economic tools, such as those described in Hauer (1971) can be used to illustrate tradeoffs between these parameters. As an example, we consider the tradeoffs between service frequency and capacity. Although others exist, we postpone a detailed discussion to Section 6.

Determining optimal frequency of service is a complex and ongoing issue for transit agencies. Although an infrequent service schedule may satisfy total passenger demand from a theoretical perspective, in practice it will also increase passenger dissatisfaction and motivate the search for other transportation options. In fleeting models, frequency is set by specifying a maximum headway. In low demand situations, this provides an incentive for the selection of smaller buses, as they provide the same frequency of service at lower cost than larger buses of the same type. However, smaller buses have less capacity per bus, and thus run at higher load factors. When load factor becomes critical (at a certain number of passengers, or ostensibly when no one else is able to fit on the bus), either no more demand can be served, or another bus needs to be added to the line. For the buses considered in the numerical example presented herein, the tradeoffs between bus frequency and capacity are explored further in Fig. 1.

The slope of each line indicates relationships between frequency (per hour) and the amount of passenger demand that can be served. Horizontal and vertical lines represent example thresholds for minimum capacity necessary to meet demand and maximum headway set by policy respectively. By observing the number of marks in each line to cross each threshold, the number of buses required to meet a threshold is determined. For example, in Fig. 1, “low” demand can be served by all of the bus types, except HFC, with a frequency of 3–5 buses per hour (headway of 20–12 min), depending on type of bus. When a minimum frequency (maximum headway) constraint is added, the number of buses required increases. Thus, these constraints work together to form the boundary on the minimum number of buses. The frequency to capacity ratio is one aspect determining which constraints will be binding in an optimization problem. Costs of transit operations using smaller buses are more sensitive to capacity, while for an operator using larger buses, costs are more sensitive to frequency/headway policy. Although this is a simplistic relationship, these level-of-service tradeoffs illustrated in Fig. 1 are the most fundamental part of the bus fleeting problem.
3.2. Bus fleeting model formulation

A linear programming model to support the design of a bus fleet to serve a route with (round trip) service time $T$, demand per hour $P$.

Minimize: $\sum_r c_r n_r$  \hspace{1cm} (1)

Subject to:

$\sum_r s_r n_r \geq \frac{PT}{h}$ \hspace{1cm} (2)

$\sum_r n_r \geq \frac{T}{h}$ \hspace{1cm} (3)

$F_k' \sum_r [I-B_r]^{-1} \begin{bmatrix} n_r \\ 0 \\ \vdots \\ 0 \end{bmatrix} \leq e_k, \hspace{0.5cm} \forall k$ \hspace{1cm} (4)

$n_r \geq 0, \hspace{0.5cm} \forall r$ \hspace{1cm} (5)

where the decision variable, $n_r$, represents the number of buses of type $r$ to be purchased, $c_r$ is the equivalent annual lifecycle cost, and (1) is the overall cost. $s_r$ is the capacity of bus type $r$. $\alpha$ and $h$ are, respectively, the desirable (maximum) load factor and headway. Thus, (2) and (3) ensure that service requirements are satisfied. $B_r$ is a bill of materials matrix associated with bus type $r$ (in terms of direct demand for activity across all economic sectors under consideration), $[I-B_r]^{-1}[n_r, 0, \ldots, 0]'$ represents total direct and indirect economic activity associated with $n_r$. $F_k$ is a vector with components representing environmental impact along dimension $k$, associated with economic activity in each sector. Thus, each of the constraints in set (4) restricts total impact along dimension $k$ to be below $e_k$. Finally, (5) impose logical restrictions on the decision variables.

To recap the contribution of the model herein, IO models for environmental LCA (e.g.: Croft McKenzie and Durango-Cohen, 2012) are focused on term-by-term evaluation of the left-hand-side of Equation set (4). Due to space limitations, we do not elaborate further, but do refer interested readers to Hendrickson et al. (2006) for a generic discussion of the methodology, and to Croft McKenzie and Durango-Cohen (2010) for examples that include bills of materials for substitutable alternatives. In contrast, the model in (1)–(5) integrates environmental impact with economic and service consideration in the selection of $n_r$. One of the reasons we choose not to pre-multiply the parameters in the left-hand-side of (4) is to emphasize that one of the strengths of the modeling framework is that it supports analysis of perturbations, due to technological developments, in the elements of $B$ on the outputs. We also note that the framework supports similar models such as minimizing environmental impact (across a given dimension, e.g., greenhouse gas emissions) subject to budget constraints.

In the following sections, we consider numerical examples where the above model is used to design bus fleets for a number of scenarios.

4. Data and sources

The data used in this study were obtained from a series of recent demonstration studies on alternative fuel buses conducted by the National Renewable Energy Laboratory (NREL), a subsidiary of the United States Department of Energy (DOE). Data sources are summarized in Table 1. Using field data from bus operations poses challenges, but has the potential to reveal insights. The use of a common and explicit set of assumptions to collect data allows for reasonable comparisons across the studies. It also provides a benchmark for future data collection efforts.

In this study, we consider 4 types of transit buses: Diesel, Compressed Natural Gas, and Hydrogen Fuel Cell (HFC). The parameters in the present study were generated by averaging over the data collected from each of the demonstration studies. The scope of the life-cycle assessment and costs includes both bus manufacturing and operations. Operating characteristics such as capacity, fuel consumption, maintenance requirements; and manufacturing characteristics such as size, technical components, batteries, power-train, and exhaust systems, are included. The parameters corresponding to these characteristics were taken/adapted from the NREL studies, or are based on assumptions inspired by the available data. They are summarized in Table 2.

5. Numerical examples

We begin this section by outlining the scenarios considered for analysis. The following assumptions, some implicit in the model, apply throughout (unless stated otherwise):

\footnote{$A'$ represents the transpose of matrix/vector $A$. $I$ is an identity matrix.}
Passenger demand is fixed and constant – it does not change based on day of the week or time of day.

Buses are always able to travel at the same speed, as conditions of vehicle flow are not dependent on the number of transit vehicles on the route or time of day.

Boarding and alighting times are fixed and not dependent on how many passengers are boarding and alighting at each stop.

Maintenance, fueling, and crew issues do not affect the fleeting problem – that is, the daily bus service can be completed without shift changes, fueling stops, or repairs.

The length of the route is such that the yearly mileage of the bus is 26,000 miles and each round trip route takes 120 min.

The infrastructure and personnel for each bus type is already in place.

The life of the bus is 15 years.

A discount rate of 6% is used.

The maximum passenger load factor is the manufacturer’s specification of the number of seated and standing passengers that can fit on the bus.

Transit buses are purchased for a single line. Bus switching is not available.

If passengers are not able to board the bus, they will wait for the next available bus.

5.1. Scenarios

The five scenarios below are intended to show the effects of a variety of parameter and threshold changes on the optimal solution and to gain insight into the tradeoffs between buses, that can be applied to other fleeting problems. In Scenario A, the fleet mix is optimized based solely on maximum headway and passenger demand. In scenarios B-D, the four environmental impacts constraints are considered: greenhouse gasses (GHG), nitrous oxides (NOx), particulate matter (PM), and total energy. In Scenario B, the
tolerances are decreased proportionally for each impact, resulting in an overall reduction of emissions. In Scenario D, NOx alone is restricted, while other environmental impacts have modest tolerances. The remaining two scenarios, C and E, examine the effects varying passenger demands and headway, respectively. Rather than representing a specific bus route, the objective is to highlight the framework’s capabilities to capture the inherent tradeoffs.

5.2. Numerical results

The optimization model presented in Section 3.2 was used to select fleets for each of the scenarios in Table 3. The results appear in Table 4. The first row shows lifecycle costs of each scenario, which include purchase and discounted operating costs. The next box shows the fleet mix for each optimal solution. The third shows environmental impacts. In some scenarios, levels of GHG and NOx reach the point where the respective constraints become binding. In these cases, the shadow prices are reported. The final box summarizes other parameters. Again, when the headway and demand levels reach the point where constraints become binding, the shadow prices are included.

5.2.1. Scenario A – Baseline

The first scenario focuses on servicing the passenger demand (4 pax per minute) with a maximum headway constraint (20 min). The optimal solution is to run 6 diesel buses, 20 min apart, at a lifecycle cost of $4.66 m. Headway (Eq. (3)), is the only binding constraint, and the load factor\(^2\) is 93%. The shadow price indicates that the decision maker would be willing to pay (save) at most $38,869 to reduce (increase) the headway by one minute.

5.2.2. Scenario B – Fleeting with environmental constraints

In Scenario B, the environmental constraints are introduced by setting an allowable tolerance at the level in Scenario A, and

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\(^2\) The percentage of occupied sitting and standing places at the place where the demand is the highest.
decreasing GHG and NOx till a minimum level is reached. Although the lifecycle cost does not change significantly, the fleet mix changes to use CNG buses, as these buses have more favorable in terms of environmental repercussions. The load factor increases slightly to 95%. The shadow price for the headway increases, indicating an increased willingness to pay to relax this constraint. Furthermore, the shadow prices for GHG and NOx indicate that the decision maker would be willing to pay to increase these tolerances as well.

5.2.3. Scenario C – Decreased headway

In Scenario C, the maximum headway is decreased to 15 min. This initially makes the problem infeasible, because the environmental tolerances are violated. Each constraint needs to be increased by 13–30%, with the greatest increase in total energy in order to cover the amount of additional energy required to manufacture and use 8 buses instead of 6. The minimum cost solution is to use 4 diesel, 3.13 CNG, and .9 HFC buses, and the lifecycle costs increase to $6.32 m. The load factor actually decreases as more buses are used to carry the same demand, even though some buses have less capacity. Again the shadow price for headway increases, and in this scenario reaches its highest level at $62,451.

5.2.4. Scenario D – Constrained NOx emissions

Nitrous oxide pollutants a product of many transportation modes and are the building blocks of smog, acid rain, and contribute to ozone depletion and global warming. Currently, National Ambient Air Quality Standards regulate the amount of NOx that can be present in the outside air, and high traffic volumes contribute to non-attainment in many areas. In Scenario D the primary motivation of the decision maker is to minimize the NOx pollutants from the bus fleet.

When the NOx threshold is lowered, the optimal solution is to use more HFC buses, which has the lowest lifecycle NOx emissions (see Table 2) However, due to the small passenger capacity of this bus, only 0.7 buses are replaced with HFC buses before the load factor increase to 100%. Any further increase in demand or frequency will push the solution over the NOx threshold. Shadow prices on multiple variables reflect the tight constraints in this scenario, and can be used to value the tradeoffs that can potentially be made between different restrictions.

5.2.5. Scenario E – Increased passenger demand

How much can passenger demand be increased without increasing NOx emissions in the optimal solution? Scenario E addresses this question. A strain is placed on capacity by increasing the passenger demand by 25% to 5 passengers per minute. As demand is increased, more buses will be required. However, as the proportion of HFC buses is increased, capacity will shrink. More HFC buses are needed to serve the same demand than any other type, increasing overall emissions, thus HFC buses are not used in the optimal solution. Perhaps surprisingly, in this scenario the optimal solution is to serve the route entirely with diesel buses. The minimum level of NOx is 56 MT. Even though diesel buses have higher per-bus emissions, they are the only option with enough capacity to serve 5 passengers a minute. Because no buses can serve the same amount of passengers as diesel buses without an increase in GHG or NOx emissions, the minimization of these factors is also implied in this solution.

5.3. Sensitivity analysis

As stated, one of the key advantages of the proposed framework is the capability to conduct sensitivity analysis as described below.

5.3.1. Reduced costs

The reduced cost is a measure of the cost decrease necessary to bring a variable into the optimal solution. For each variable not part of the optimal solution in Table 4, a reduced cost is given in Table 5. Reduced cost is one method to determine the significance of the differences between different technologies, and the prices at which these technologies will become part of the optimal solution, i.e. be cost effective. Depending on the scenario, the reduced cost for each bus can range from <5% to >100% the cost of the bus. In the former case, this may be accomplished by subsidizing the more environmentally friendly but less cost-effective technology for a small cost. In the latter case, the cost serves as a barrier to entry, indicating that the technology is not a viable option for a particular situation.

5.4. Time of day tradeoffs

Although most research focuses on peak periods, off peak periods present an interesting challenge to modelers and transit operators alike. Often, demand and acceptable level of service are quite different from the peak period. Generally, the assumption is that buses should run less frequently in the off peak period. However, Jansson (1980) found that social cost minimization requires more frequent bus service than is generally accepted, and makes the case that in some scenarios the frequency of buses in the off peak period should match that of the peak period.

This section examines the problem of optimizing buses for the off peak period. Since demand is lower, it might be feasible to run

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3 A “partial” or fraction of a bus can be obtained in the real world by running each bus less often than the others. For example,.5 of a bus means that the bus in question would run half as often as the other buses. The remainder of the bus’s time could then be used to serve other needs, such as running on alternate routes.
smaller, more efficient buses if they are available. Two scenarios are examined, one where the buses are a subset of those available for the peak period, and one where the buses can be chosen for the off-peak period separately. Buses from Scenario C are chosen to illustrate the most possible trade-offs. Secondly, the question of minimum emissions in the off-peak period is examined.

### 5.4.1. Description of off-peak scenario parameters and objectives

Two cases are examined. In the first case, the fleet has already been optimized for the peak period with the solution for Scenario C in Table 4. The pre-optimized mix of buses includes 4 diesel buses, 3.1 CNG buses, and 0.9 HFC buses. In the second case, the buses will be optimized for the off-peak period only; the solution is not constrained to buses available in Scenario C.

Unlike the peak period, both cases consider the optimal operational cost, that is, assuming that capital and fixed costs are sunk; the buses are already purchased. Secondly, for each case, a model is run to minimize lifetime NOx emissions by modifying the linear program so that the environmental constraint for NOx is moved to the objective function. This formulation can be found in Croft McKenzie (2013). Although NOx emissions are the focus of this paper, any environmental or level of service parameters can serve in the objective function, depending on the qualities of the problem.

To model the off-peak period, passenger demand is assumed to be 50% of during the peak period. Headways are increased to 30 min (double that in the peak period), and then 40 min.

### 5.4.2. Time of day tradeoff results

Fig. 2 displays the optimal mix of buses, operational cost, lifecycle cost, and lifecycle NOx emissions for four off-peak models. The first set of columns shows results for a 30 min headway, and the second set shows results for a 40 min headway. For each, minimized operational cost and minimized NOx emissions are modeled. The first row shows the “Any bus” scenario, while the lower row shows the results if the bus types are constrained to those in Scenario C.

Results show that even though allowing the choice from a wider set of buses can lower operational cost, it actually causes an increase in lifecycle cost in all cases. The hybrid bus, which was not used in any of the peak scenarios, is used due to its low operational cost when optimizing for the off-peak period alone. When minimizing NOx, the lifecycle cost is greatly increased. However, when minimizing cost, even though the “Any bus” and constrained scenarios have different mixes and operational costs, the lifecycle costs are similar (and lower in the constrained scenario). Many costs of owning a mixed fleet, such as increased training, maintenance, and infrastructure costs, are not included in this analysis, which would further increase the costs of running a mixed fleet.

### 6. Discussion, conclusions, and future research

We present an optimization model to support the design of transit bus fleets while accounting for tradeoffs among costs, level-of-service requirements, and restrictions on emissions and energy consumption. Specifically, the objective considered herein is to minimize acquisition, operation, and disposal costs. Constraints in the model are used to impose a minimum frequency of service, i.e., headway, and to ensure that capacity satisfies passenger demand. Environmental impact is considered along the following dimensions: energy consumption, and emissions of greenhouse gases, particulate matter, and nitrous oxides. To illustrate the framework, we consider scenarios of designing bus fleets consisting of 4 bus types differing in their fuel-propulsion technology and ensuing design and operational characteristics: ultra-low sulfur diesel, hybrid diesel-electric, compressed natural gas, and hydrogen fuel-cell. Data for the study are from the National Renewable Energy Laboratory transit bus evaluation and demonstration studies conducted over the period 2003–2009.

Methodologically, the work bridges applications of Economic Input-Output analysis to conduct environmental lifecycle assessment with seminal work in production economics, where such analysis relies on linear programming for the purpose of evaluation and selection among alternatives, as well as to support sensitivity analysis. From an application perspective, the framework provides a structured approach to capture and assess potentially complex tradeoffs in a variety of scenarios. Among the observations and insights that stem from our analysis, we note:

- First and foremost, the model highlights the sensitivity of efficient fleet mixes to problem specifications and to the parameters considered in each of the scenarios.
- For example, the mix of transit vehicles in the peak scenarios appear to be driven by the need to satisfy passenger demand, i.e.,

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4 Again we look at the single line problem only, so bus swapping is not allowed; the route must be run using selections from only this mix of buses.
diesel buses with the largest capacity appear in optimal solutions for all scenarios considered. However, this is only part of the story, as the reduced costs suggest that small reductions/subsidies of on the order of 5–10% of the purchase price of CNG and HFC buses would result in changes in the optimal fleet mix, and consequently, in the optimal number of vehicles in 3 of 4 relevant scenarios.

In our analysis, modeling the off-peak scenario was a chance to examine different problem specifications – alternative objective functions either seeking to minimize NOx emissions or operational costs, or constraints on the available alternatives – “Any Bus” vs. “Pre-Optimized” set. Generally, these scenarios favor the advanced technology buses with lower operational costs, i.e., hybrid and HFC buses. However, when minimizing cost, even though the “Any bus” and constrained scenarios have different mixes and operational costs, the lifecycle costs are similar (and lower in the constrained scenario). Many costs of owning a mixed fleet, such as increased training, maintenance, and infrastructure costs, are not included in this analysis, which would further increase the costs of operating a mixed fleet. Therefore, even though the costs of running the buses optimized for the peak period may look higher on the balance sheet, the overall costs of running this type of fleet will be minimized.

- Overall, HFC buses, which are generally known for their environmentally friendly operation, save emissions only if the demand is low, because the emission per passenger are actually very high. Perhaps surprisingly, diesel buses are some of the best performers in terms of emissions per passenger for all categories except PM, and performed well in reducing overall lifecycle costs and emissions in a variety of scenarios.

- Jansson (1980) showed more frequent service, even in the off peak period, minimized social costs; however, a corresponding increase in both capital and labor costs is incurred. Off peak analysis in this study shows that smaller buses with more frequent service can allow a high level of service yet may not always cause large increases in capital and operating cost, especially when demand is high and environmental thresholds are tight.

The limitations of the model, including restrictive assumptions that motivate additional research:

- While we use the model successfully to generate insights about tradeoffs in purchasing and operating transit buses, directions in which the model can be updated/extended to reflect other (practical) considerations are discussed below. A few of these directions are not unlike considerations that arise in any type modeling.

Formulating the decision variables as continuous rather than discrete simplifies the computation, provides an established analytical framework to conduct sensitivity analysis, but leads to solutions that may not be readily implementable. Similarly, there is an argument to be made that a multi-objective optimization model would better capture the inherent tradeoffs in the problem. Omissions in the objective function include the costs associated with deploying infrastructure to support transit vehicles,
increased costs associated with operating heterogeneous bus fleets, among others. Some of these costs can be difficult to estimate. For example, they may include additional inventory carrying costs for spare parts that cannot be pooled across an entire fleet. In any case, the optimal solution to the fleeting problem provides a benchmark for the performance of alternative fleets that may be under consideration, i.e., the objective function and constraints of the model can be evaluated for arbitrary fleets and the results can be compared to those obtained with the optimal fleet mix.

Relative to synergistic models in bus scheduling or in the design of transit networks, there is room to improve the representation of demand and user costs in the model, as well as to extend the formulation to the case of multiple bus routes. For example, rather than imposing maximum load factor and headways exogenously, it may be possible to include comfort and waiting in a user cost function, and use it to optimize the aforementioned parameters. Other possible improvements in the model might be to specify an endogenous demand function that depends on the transit fare, or having travel times, i.e., dwell times, depend on the number of passengers.

Relative to models used to study the adoption of advanced technologies in other contexts, the model could be improved by considering how demand or operating characteristics might evolve, and by formulating the problem as a dynamic optimization model.

- The data used in the study are from field demonstration studies conducted 10–15 years ago. We chose these data because they are publicly available, and because they were collected under explicit and consistent assumptions, which allows for a more reasonable comparison among the buses. Even though, qualitatively, the tradeoffs inherent in present-day buses are not radically different, it would be relevant to update the model parameters to reflect recent technological developments in propulsion technologies, e.g., batteries and electric motors of Hybrid buses, emissions control systems for diesel buses, hydrogen fuel cells, etc. We are not, however, aware of efforts by the NREL or other organizations aimed at conducting such studies in a systematic fashion.

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