Multicriteria asset management strategies for mixed transit fleet

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ABSTRACT

Agencies and policymakers require equitable and optimal allocation of funds among transit agencies for not just regular operations and maintenance, but also for asset management including purchase of new buses and rehabilitation of aging fleet. The paper proposes a hierarchical structure of resource allocation model where federal funding is routed through the state, and ultimately to local transit agencies. The multicriteria framework encompasses multiple dimensions such as selection of different improvement program options (rehabilitation, remanufacturing, and replacement) of a mixed transit fleet spread over a temporally continuous planning period. It leverages optimization models for capital allocation among transit agencies in the state. Four sub-models are developed— two maximizing passenger miles traveled, and the other two maximizing the total fleetwide remaining life, all under agency-specific budget, capacity and policy constraints, and planning objectives. They are applied on real-world data from set of transit agencies spread across the state of Tennessee, containing a heterogenous fleet of 254 total buses at various levels of aging. Results indicate that by application of the framework, an average 40 percent additional mileage is generated through the planning period with the same levels of fleet size, with nearly 30 percent of the fleet receiving some form of improvement treatment per year.

Keywords: optimal resource allocation, transit asset management, rehabilitation and replacement, integer programming, branch and bound algorithm

1. INTRODUCTION

Local transit agencies often possess an aging bus fleet and must regularly allocate funds and programs for fleet maintenance and upkeep. However, they must do so with limited resources, depending most commonly on federal support. Recent surveys from 2012 indicate that public transit agencies spent close to $16.9 billion on capital investments, out of which annually authorized federal funding comprised 36 percent of these capital expenditures (FTA, 2015). For the remaining share, they rely on state and local governments. Two main objectives for these funds include full replacement of old buses, and/or rehabilitating some fleet to add extra service life. Ideally a bus at the end of its service life needs to be replaced, but it is not always easy for many states to procure the matching funds for new buses for their agencies. In such cases, various rebuilding alternatives are considered which, however, are not long-term solutions.

Decision-making regarding replacement and timely rehabilitation thus becomes a critical management aspect which requires a robust fund allocation mechanism to support such decisions. Complete replacement may be the most desirable option from a quality perspective, but keeping budget constraints in mind, this option is not always readily available. Thus, the real challenge for agencies lies in finding an optimal balance between the fraction of the total fleet selected for rebuilding and replacement. These challenges form the key motivation for the current study, and the problem addressed here is typical of many state Departments of Transportation (DOTs) in the U.S. that financially support their constituent transit agencies.

Several studies have explored the economics of purchasing new buses versus rebuilding of existing buses. Khasnabis and Naseer (2000) found that it may be cost-effective to rebuild an existing bus by extending its effective life by a few years at a fraction of the procurement cost of a new bus, but only up to a certain limit. Another study developed a two-stage linear programming model to allocate resources among different improvement programs (Khasnabis et al. 2004). A few more recent studies explored optimization of different surrogates such as maximizing service life including Remaining Life (RL) of the overall fleet

(Mishra et al. 2010), maximizing the total system weighted average remaining life (TSWARL) (Mathew et al. 2010), and minimizing net present cost (NPC) of investment (Mishra et al. 2013). The current study builds upon these previous models, but from the operations point of view uses a new approach by optimizing another surrogate of quality of service— total passenger miles traveled (PSM) and uses a mixed fleet (varying size and capacity) rather than a homogeneous one. The proposed framework addresses three key dimensions for statewide transit fleet management, including choice of rebuild/replace option, proportioning funds across agencies, and disbursement over time. The model is formulated as an asset management problem that can be interfaced with the state DOT's long-term strategic transit plans.

The remainder of this paper is organized as follows: Section 3 covers the methodology, including a general overview of the framework, and the detailed optimization model formulation. Section 4 presents a real-world case study application of the proposed model, and covers a numerical analysis of the solutions method and the results obtained therein. Section 5 concludes the paper by summarizing the study contributions and implications for policy and practice, and describes potential future research avenues.

2. LITERATURE REVIEW

The literature review primarily focuses on the strategic resource allocation for fleet replacement and rebuilding programs. Resource allocation under fixed budget and competing requirements are covered in many different areas including operations research, manufacturing, finance, and transportation infrastructure (Ross 2000; Sheu 2006; Melachrinoudis and Kozanidis 2002; Ahmed 1983). Studies covering asset management problems from the transit planning domain also include a variety of topics, such as resource allocation to various agencies (Forkenbrock and Dueker 1979; Forkenbrock 1981), determination of location, size and number of transit centers (Uyeno and Willoughby 1995), allocating fleets in transportation networks (Diana, et al. 2006), and the dilemma of purchasing new buses or retiring old buses (Simms et al. 1984; Khasnabis et al. 2002). Some studies exploring fleet management solutions covering the needs of replacement and/or rebuilding of buses include Balzer et. al (1980), Rueda (1983), and Davenport (2005).

These problems have typically been formulated as linear programming or non-linear programming, integer, mixed integer and dynamic programming models. (Ahmed 1983; Ariaratnam and MacLeod 2002; Srour et al. 2006; Uyeno and Willoughby 1995; Melachrinoudis and Kozanidis 2002; Kozanidis and Melachrinoudis 2004). Solution methods for these optimization problems are chosen depending on the nature of the problem, although traditionally, they are solved by various forms of gradient search methods (Deb 2001) that assume the search space to be uniform and unimodal for a unique solution. Since most practical problems encountered in practice happen to be non-convex, some other ways to solve them are employed, including Genetic Algorithm (GA), a general purpose robust solution algorithm (Mathew and Mohan, 2003; Karlaftis et al. 2007; Deb 2001), and Branch and Bound Algorithm (BBA) to deal with integer variables and constraints (Haggag 1981; Pillai 1998; Horn 2004; Mishra et al. 2013).

The literature lacks studies that develop resource allocation of mixed transit fleet to answer the question— "*with limited budget, how to allocate funds to constituent agencies to maintain at least the same number of fleet in a planning period, when each agency has a variety of buses (by age and size), and how to decide whether to replace, rehabilitate or to rebuild the existing buses.*" This paper develops a comprehensive mathematical programming model for funding allocation among a set of transit agencies for fleet management. A Branch and Bound Algorithm (BBA) is used as the solution method given its scalability for handling large problems.

3. METHODOLOGY

3.1. Modeling Approach and Assumptions

The paper represents a hierarchical structure of U.S. federal support for transit agencies, where the Federal Transit Administration (FTA) allocates the funding among state departments of transportations (DOTs, (Tennessee DOT, TDOT in this case)), which further distribute it among their constituent local transit operators. The funds are meant to keep the fleet in productive and safe operation within its minimum normal service life. Buses reaching their service life are eligible for replacement using these funds. However, under many practical scenarios, operating budgets may not be sufficient to guarantee funds for a full replacement, or the state DOTs are unable to furnish matching funds. In such cases funds may be allocated to only partially replace a part of the fleet, and partially rehabilitate the remainder using a variety of rebuilding program options, thus extending the service life by a few years. The remaining life can be extended by nearly four to ten years depending on the nature of the program and the size/characteristics of the bus, and studies such as Khasnabis et al. (2003) have shown that remanufacturing/rehabilitating of buses, if done properly, can be a cost-effective option.

Four total maintenance options are considered in this study, including three levels of rehabilitation (REHAB1, REHAB2, REHAB3) each extending the service life by a limited number of years, and one complete replacement option. In terms of size, buses are classified into small, medium, and large based on its capacity, in accordance to a 2007 FTA study (FTA, 2007). The whole statewide fleet is considered where 30% of the fleet is categorized as small, 40% as medium, and the remaining 30% as heavy. Table 1 shows a summary of the options considered, their expected benefits and costs associated with them. The costs of implementing each option vary by type of bus based on capacity. The information is based on real-life or observed costs reported by the FTA. Fleet maintenance options above represent general bus rehabilitation and rebuilding practices, that have been studied in the literature on the needs and experiences of the transit industry (Balzer et al. 1980; Felicetti 1985; Khasnabis and Naseer 2000).

Table 1

Fleet maintenance options and investment costs (adapted from FTA, 2007).

Maintenance Type *(Years)*	Cost Range by Fleet Size (*Seat Range*)		
	Small	**Medium**	**Heavy**
REHAB1 *(2 years)*	\$3,000-\$6,600 *(3-12 seats)*	\$10,000-\$20,000 (*13-24 seats*)	\$36,000-\$106,200 (*25-50 seats*)
REHAB2 *(4 years)*	\$5,400-\$11,880 (*3-12 seats*)	\$18,000-\$36,000 (*13-24 seats*)	\$65,000-\$191,750 (*25-50 seats*)
REHAB3 *(6 years)*	\$7,500-\$16,500 (*3-12 seats*)	\$25,000-\$50,000 (*13-24 seats*)	\$90,000-\$265,500 (*25-50 seats*)
REPLACE *(8-12 years)*	\$15,000-\$33,000 (*3-12 seats*)	\$50,000-\$100,000 (*13-24 seats*)	\$180,000-\$531,000 (*25-50 seats*)

Some working assumptions are made regarding implementation of rehabilitation and replacement policies. It is assumed that over the course of a planning horizon, for an individual bus, any rehabilitation or replacement option may be implemented only once. A bus reaching the end of its remaining service life must receive some form of maintenance. Also, however, a bus cannot receive more than one form of maintenance in the same year. In terms of spending, it is assumed, that the spending costs may not exceed the available budget though carry-over of funds from a future year are allowed as long as the total allocated cost does not exceed the planning period budget. The assignment of a particular maintenance option to a bus in a certain year is a decision variable that is decided by the optimization problem, and a bus may receive more than one rehabilitation option before being selected for complete replacement.

A few different planning options are modeled and presented for comparison, represented through four sub-models. In the first one, a fleet may be selected for a maintenance option a few years before the end of its service life. This scenario is mileage-based and maximizes PSM, and is categorized under Total Passenger Miles Maximization Based Allocation (TPSMBA). It is henceforth referred to as "PSM Scenario". Next, a more stringent strategy is evaluated wherein a bus is only eligible to receive improvement when it is at the end of the remaining life (or service life is nearly zero). This scenario is a Minimum Normal Service Life Based Allocation, and thus referred to as the "PSM-MNSL Scenario". The policies under this scenario are relatively more conservative than PSM. The third and fourth scenarios are service life-based, and are categorized as Minimum Normal Service Life Based Allocation (MNSLBA). The third scenario maximizes the total remaining life (RML) of the fleet and is thus referred to as the "RML Scenario". The fourth scenario is again a relatively more constrained where is the objective is to still maximize Total Remaining Life like the third scenario, but a bus in this case is only eligible to receive maintenance when its remaining life is depleted. This scenario is thus referred to as the "RML-MNSL Scenario". Ultimately, a "Do-Nothing Scenario" is also evaluated where the agency does not use any form of resource allocation framework. The relative benefits in terms of costs, surplus, and additional passenger miles generated, and compared across the four different scenarios.

3.2. Model Formulation

3.2.1. PSM Scenario

The model is formulated as an optimization problem where the objective is to maximize PSM. Since each option adds some years to the service life of a bus, PSM quantifies the effectiveness of the maintenance in terms of additional passenger travel made possible by the treatment. It is thus a resulting surrogate of service life extension of a bus receiving maintenance treatment of any kind as mentioned above. The model is a variant of a resource allocation problem of the fleet for all the agencies over the entire planning period, subject to budget, demand, rebuild, and non-negativity constraints. This formulation is given below preceded by an explanation of notations:

Notation

Sets

I	Active buses in the fleet
M	Years within the analysis period (planning horizon)
K	Available maintenance options

Parameters

B	Annual state DOT budget
ρ	Ratio of maximum allowable expenditure versus annual budget
c_i	Capacity of bus *i*
a_i	Current active miles of bus *i* as of the first year of analysis
y_i	Current age of bus *i* at of the first year of analysis
r_{im}	Current remaining life of bus *i* at year *m*
μ	Interest rates for funds borrowed
cs_m	Cumulative surplus at year *m*
l^k	Additional life generated by a maintenance option *k*
j_m^k	Cost of maintenance option *k* at year *m*

PSM — Total additional passenger miles generated through year *m* of planning

θ_{im} — Parameter for MNSL, 1 when the remaining life is zero, and zero otherwise

Decision Variables

$x_{im}^{k} = \{0,1\}$ — 1 if improvement *k* is implemented on fleet *i* at year *m* year of the planning period, and 0 otherwise

The PSM Scenario is formulated as follows:

Maximize:

$$PSM = \sum_{m=1}^{M}\sum_{i-1}^{I}\frac{c_i a_i}{y_i} + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K}\frac{c_i a_i x_{im}^{k} l^{k}}{y_i} + \sum_{i=1}^{I}\frac{c_i a_i}{y_i}(r_{i1} - M) \qquad \text{Equation 1}$$

subject to:

$$\sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K} x_{im}^{k} j_{m}^{k}(1+\mu)^{(m-1)} \leq \frac{(1+\mu)^{M}-1}{\mu}B \qquad \text{Equation 2}$$

$$\sum_{m+1}^{m+l^{k}-1} x_{im}^{k} \leq x_{im}^{k}\left(l^{k}-1\right) \quad \forall\, i \in I, m \in M, k \in K \qquad \text{Equation 3}$$

$$\sum_{k=1}^{K} x_{im}^{k} + r_{im} \geq 0 \quad \forall\, i \in I, m \in M \qquad \text{Equation 4}$$

$$\sum_{k=1}^{K} x_{im}^{k} \leq 1 \quad \forall\, i \in I, m \in M \qquad \text{Equation 5}$$

$$\sum_{m=1}^{M} x_{im}^{k} \leq 1 \quad \forall\, i \in I, k \in K \qquad \text{Equation 6}$$

$$r_{i(m+1)} = r_{im} - 1 + \sum_{k=1}^{K} x_{im}^{k}\, l^{k} \quad \forall\, i \in I, m \in M \qquad \text{Equation 7}$$

$$cs_m = B - \sum_{i=1}^{A}\sum_{k=1}^{K} x_{im}^k j_m^k + cs_{m-1}(1+\mu)\ \forall\, m \in M \qquad \text{Equation 8}$$

$$cs_m \geq -B\rho \quad \forall\, m \in M \qquad \text{Equation 9}$$

$$x_{im}^k = \{0,1\}, \forall\, i \in I, m \in M, k \in K \qquad \text{Equation 10}$$

The objective function in Equation 1 maximizes PSM generated from the maintenance options. Equation 2 ensures that the cost for the entire improvement program must not exceed the total budget. Equation 3 state that one fleet cannot receive any improvement during the extended years due to the last improvement. In other words, the constraint prevents a bus from receiving a new improvement treatment until it completely exhausts the benefits it gains from a previous treatment option. Equation 4 addresses the policy where a bus reaching a remaining life of zero must receive improvement. Equation 5 restraints that no more than one maintenance option may be implemented on a bus in a given year. Equation 6 limits the number of maintenance options that a bus can receive over the planning period to one. Equation 7 develops the linkage between the growth in remaining life as a result of the benefit of improvement. Equation 8 explains the compounded growth of the budgetary cumulative surplus from the previous year to the current year. Equation 9 is a budgetary constraint indicating that funds borrowed cannot exceed the available credit line or budget. Equation 10 defines the decision variable as binary variable where 1 indicates that an improvement measure was implemented, and zero otherwise.

3.2.2. PSM-MNSL Scenario

As discussed earlier, the key difference in this scenario is that a bus is eligible to receive an improvement option only if its remaining life is zero. The parameter θ_{im} is a binary variable that take value of 1 when the remaining life is zero, and zero otherwise.

PSM-MNSL is formulated as follows:

Maximize

$$TPSM = \sum_{m=1}^{M}\sum_{i-1}^{I}\frac{c_i a_i}{y_i} + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K}\frac{c_i a_i x_{im}^{k} l^{k}}{y_i} + \sum_{i=1}^{I}\frac{c_i a_i}{y_i}(r_{i1} - M) \qquad \text{Equation 11}$$

subject to:

$$\sum_{k=1}^{K} x_{im}^{k} = \theta_{im} \quad \forall\, i \in I, m \in M \qquad \text{Equation 12}$$

And Equations 2-10 mentioned under the TPSMBA Scenario.

The objective function in Equation 11 maximizes PSM generated from the maintenance options. Equation 12 addresses the policy that the bus can only receive improvement if and only if its remaining life is zero and only one improvement can be made per situation.

3.2.3. RML Scenario

In this scenario, the total remaining life across the entire fleet run is maximized. It follows the regulation and policy of the PSM scenario, the only difference being the objective function.

RML is formulated as follows:

Maximize

$$RML = IM + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K} x_{im}^{k} l^{k} + \sum_{i=1}^{I}(r_{i1} - M) \qquad \text{Equation 13}$$

subject to: Equations 2-10 mentioned under the PSM Scenario.

The objective function in Equation 13 maximizes RML benefited from the maintenance options

3.2.4. RML-MNSL Scenario

In this scenario, again the total remaining life across the entire fleet run is maximized. It follows the regulation and policy of the PSM scenario and the only difference is the objective function. However it takes into account a relatively less flexible policy where a bus is not eligible to receive any form improvement treatment until it reaches the end of its current service life.

RML-MNSL is formulated as follows:

Maximize

$$RML = IM + \sum_{m=1}^{M}\sum_{i=1}^{I}\sum_{k=1}^{K} x_{im}^{k} l^{k} + \sum_{i=1}^{I}(r_{i1} - M) \qquad \text{Equation 14}$$

subject to: Equations 2-10 mentioned under the PSM Scenario and equation 12 under the PSM-MNSL Scenario

The next section covers the application of the above model to a real-life case study, and the subsequent numerical analysis.

4. CASE-STUDY APPLICATION AND NUMERICAL ANALYSIS

4.1. Study-Area Description and Working Parameters

The State of Tennessee is considered in this study, where 15 agencies are expected to receive funding to provide maintenance support for their aging fleet. As part of the optimal resource allocation framework, it is required to determine the most appropriate amount of funding for these agencies. The dataset containing key information on the fleet for model development and application, is obtained from the National Transit Database (NTD), maintained by the FTA. The NTD records the financial, operating and asset condition of transit systems across the country. Data obtained from the NTD for this case study are thus ‘known parameters’. Agencies report to NTD their operating fleet which includes these parameters. For a typical fleet, the manufacturing year and the capacity of the bus, total active miles counted to the point of the report, average lifetime miles are known.

In addition, certain parameters are derived from these known parameters which are used in the model development. They are listed as follows current age of fleet, remaining life of fleet, size of bus. In terms of funding, each year TDOT with an annual budget of $5 million to be further distributed among its agencies. In case of a budget shortfall, the state agency can borrow additional capital, although at an interest rate. The system revenues and surplus (if any) can then be used to repay the debt and interest. The interest rates are assumed to be 5% per year compounded annually. Also, it is assumed that the agency cannot borrow an amount more than 30% of the annual budget, to reflect credit line regulations that may cap the borrowing.

4.2. Solution Approach

The case study contains a total fleet size of 254 individual buses belonging to a total 15 transit agencies that operate on a capital-funding program administered by TDOT. Each bus has a different level of remaining life, capacity, and other characteristics. Considering these 254 buses, each eligible to receive one of the four maintenance options discussed earlier, over a ten-year analysis period, there are over 10,000 decision variables in the optimization structure, thus making it a fairly large problem. A Branch and Bound Algorithm (BBA) solution approach is used. This is an enumeration approach for solving various problems especially in discrete and combinatorial situations, including integer programming (IP). The decision variable in the current study are integers (improvement options). Application of BBA is common for transit fleet resource allocation (Mishra et al., 2013).

4.3. Results and Discussion

The results highlight both the total costs and benefits associated with implementing each planning scenario, and the variations across fleet type and different budgetary allowances.

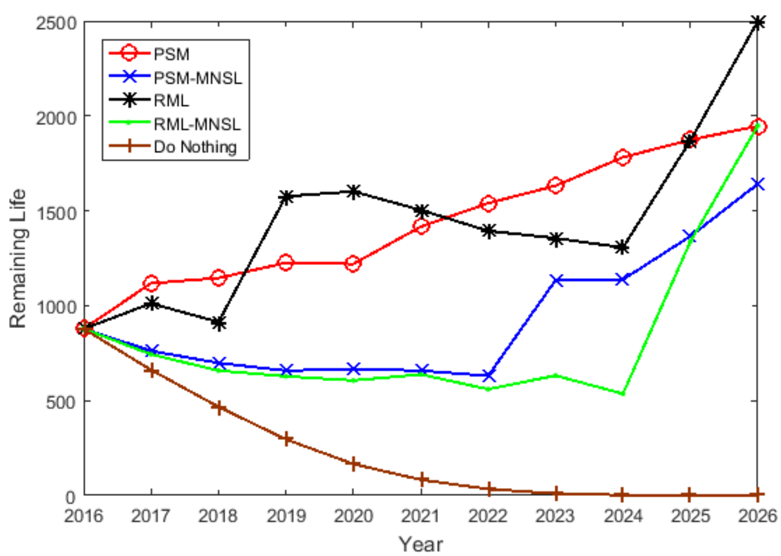
Table 2

Comparison of objective function between different models

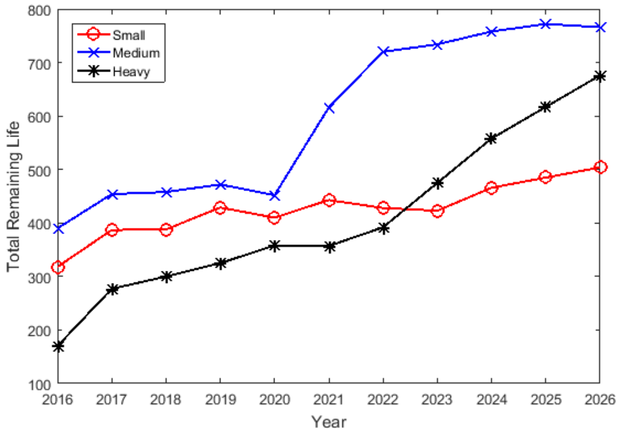
Model	Total Passenger Miles (Billions)				Total Remaining Life (Years)			
	Small	Medium	Heavy	Total	Small	Medium	Heavy	Total
PSM	0.35	0.90	5.34	6.58*	1,354	1,726	1,406	4,486
PSM-MNSL	0.33	0.87	5.00	6.20	1,244	1,606	1,332	4,182
RML	0.36	0.93	4.51	5.80	1,636	2,068	1,334	5,038*
RML-MNSL	0.34	0.92	4.60	5.60	1,388	1,774	1,326	4,488

*Notes:*Indicates the maximum value for the objective function*

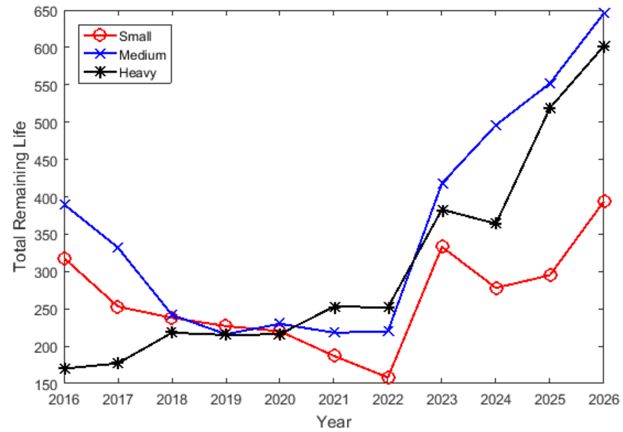
As seen in the resulting objective function values shown in Table 2, the PSM or RML relaxed scenarios perform better in terms of their objectives compare to the restricted models. The PSM scenario returns the highest benefits in terms of additional mileage generated fleetwide, whereas the RML model does the same in terms of expanding the fleetwide remaining life. Figure 2 below shows the trends of the total remaining life of the fleet under various resource allocation scenarios over the next ten-year planning period. The scenario is also compared to the do-nothing option where the agencies do not implement any maintenance program and the buses in their current form are not rehabilitated. The total remaining life of the entire fleet through the ten-year planning period under each of the planning scenarios is shown in Figure 1(a) below. Additionally, Figures 1(b,c,d,e) show the total remaining life by fleet type (under all five model scenarios).



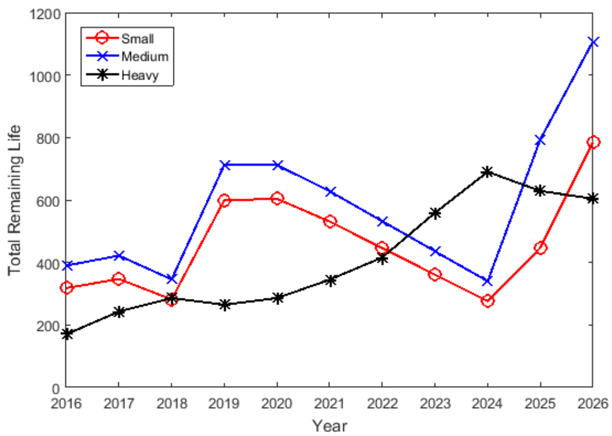
1(a) Total remaining life of mixed fleet under different planning scenarios



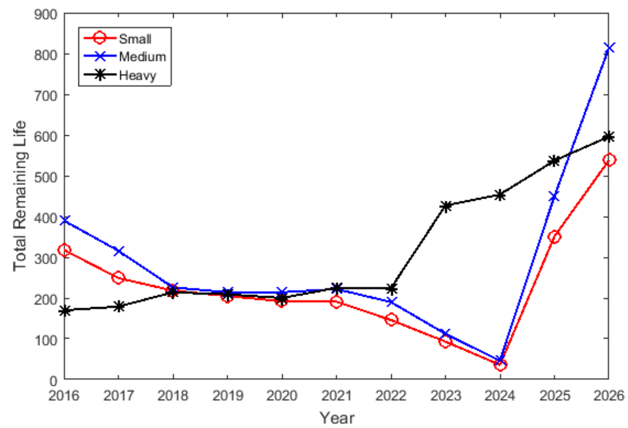
1(b) Remaining life by type of fleet for PSM scenario



1(c) Remaining life by type of fleet for PSM-MNSL scenario



1(d) Remaining life by type of fleet for RML scenario

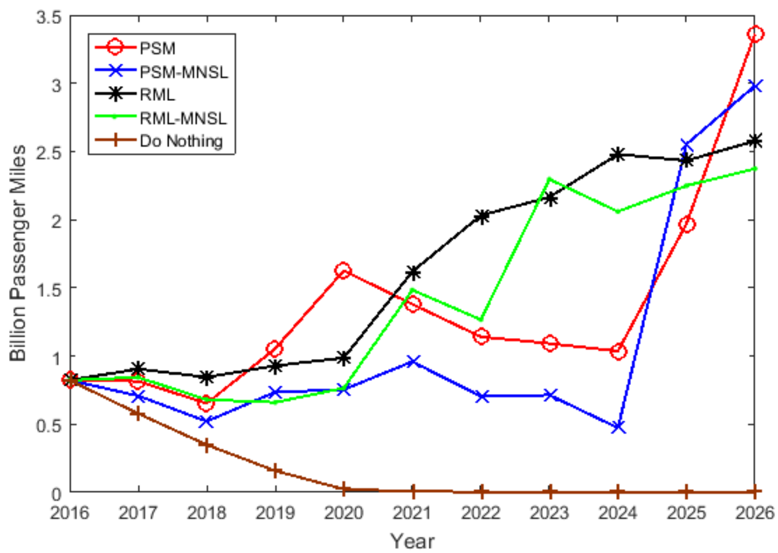


1(e) Remaining life by type of fleet for RML-MNSL scenario

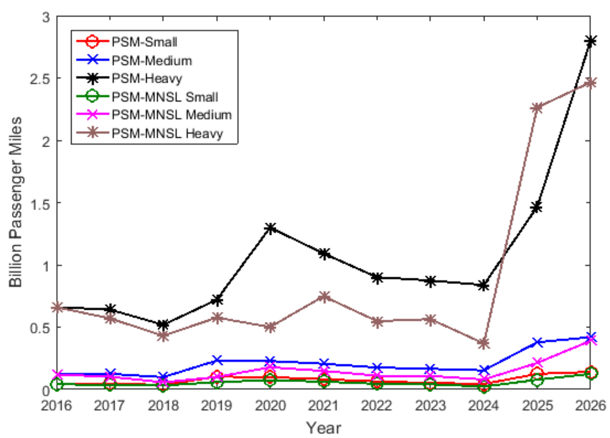
Fig. 1 Remaining life of fleet

It can be seen that under the PSM scenario where rehabilitation programs are implemented sooner, total remaining life is higher than in both scenarios. Also, in the do-nothing scenario, the total remaining life gradually drops to zero by the end of the planning period. The total remaining life of the fleet under the PSM scenario also increases at a much faster rate than the more conservative MNSL through 2025, whereas it nearly flattens out by 2021 under the do-nothing scenario because no life-extension policies are implemented. In terms of total remaining life of different fleet type, all three sizes of buses receive nearly equitable benefits through the service life under PSM scenario, however heavy buses are expected to gain the most by 2025 – an average of two years more than medium and small buses.

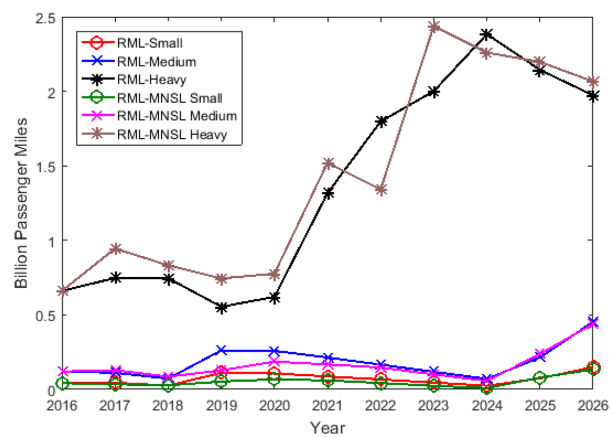
Benefits of implementing a resource allocation optimization framework are further quantified by evaluating the objective function (PSM) under various conditions, and are illustrated in Figure 2 below. The first Figure 2(a) shows the total benefits yielded in terms of total mileage the entire fleet can run each year until it is depleted. Figure 2(b) and 2(c) shows the total passenger miles added for the four planning scenarios distributed by type of fleet (there are no additional passenger miles generated in the do-nothing scenario).



(a) Total passenger miles by TPSMBA and MNSLBA scenario



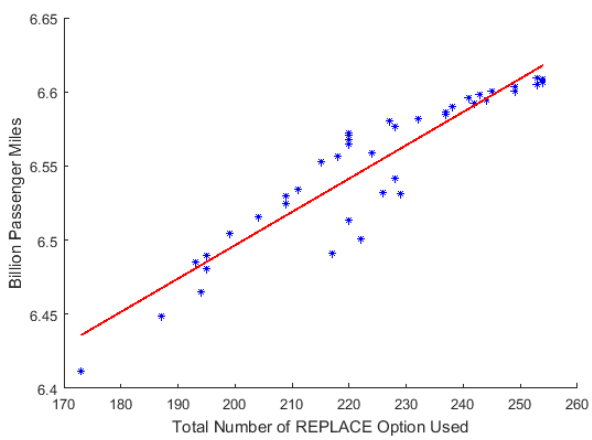
(b) Total passenger miles by fleet type
For PSM and PSM-MNSL scenario



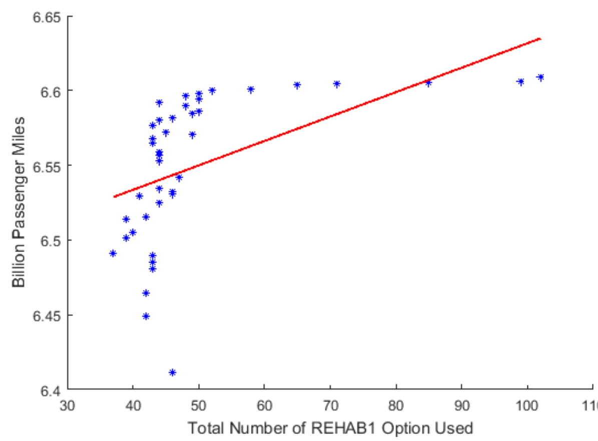
(c) Total passenger miles by fleet type
For RML and RML-MNSL scenario

Fig. 2 PSM behavior

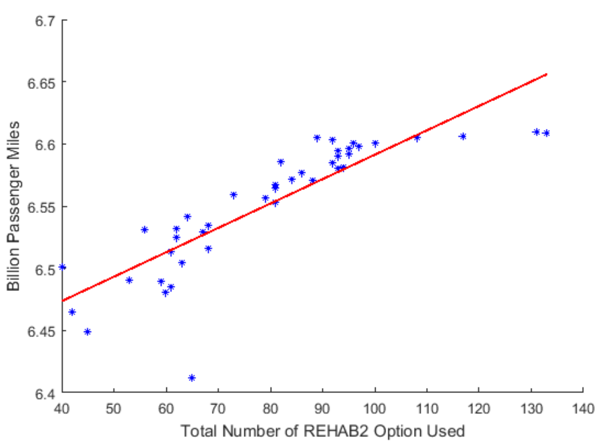
It may be noted that as in the case of total remaining life, the mileage benefits are also achieved at a faster rate under the more flexible PSM scenario. Also, heavy buses gain additional benefits over the course of the planning period compared to small and medium sized buses under four planning scenarios. Additional insights are developed on the objective function by exploring the correlation between the value of the objective function (PSM) under the PSM scenario with the number of buses improved under each of the four improvement options. These relationships between the objective function and decision variables (buses under each improvement four options) are shown in Figure 3.



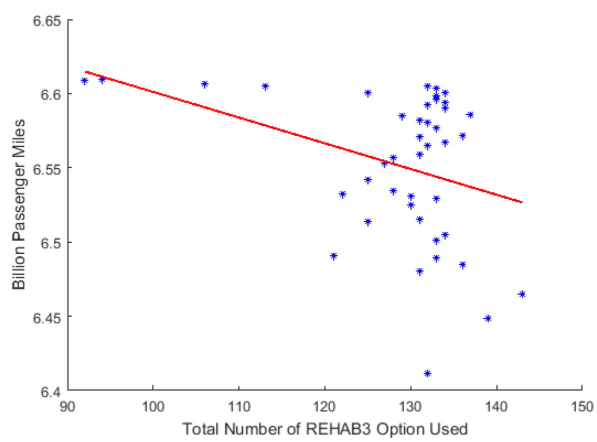
3(a) Sensitivity of REPLACE options vs. PSM



3(b) Sensitivity of REHAB1 options vs. PSM



3(c) Sensitivity of REHAB2 options vs. PSM

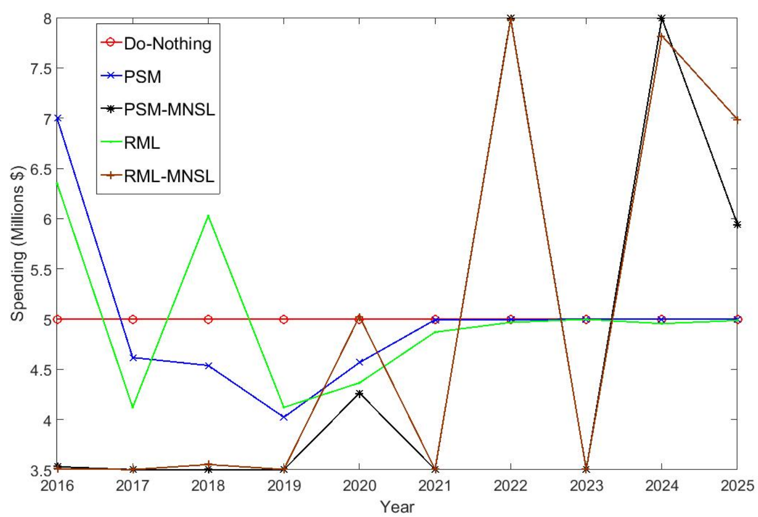


3(d) Sensitivity of REHAB3 options vs. PSM

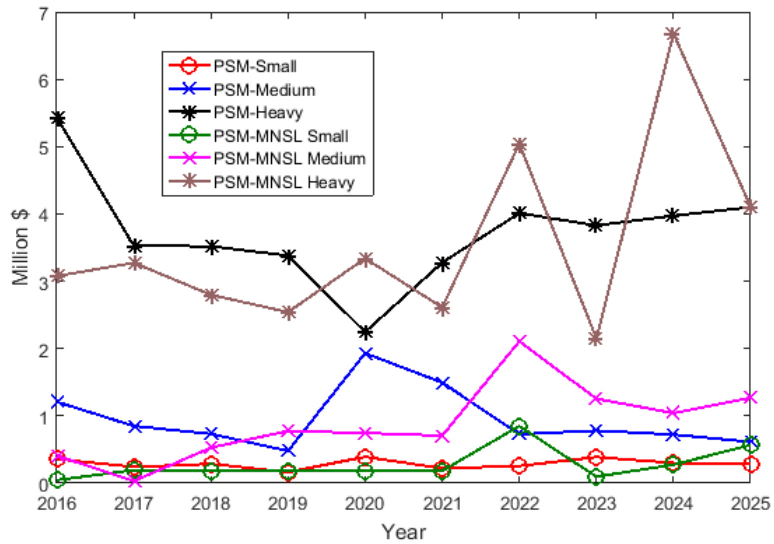
Fig. 3. Relationship of PSM with improvement options

There appears to be a positive correlation between the frequency of application of each improvement option and the objective function, indicating that higher the number of buses receiving each improvement option, higher is the total additional passenger miles gained. Hence the new systemwide benefits appear to be positively correlated with the frequency of implementation of improvement options which indicates that the model performs as desired. However, REHAB3 does not follow this trend. By observation, REHAB3 and replacement options are often the ultimate or penultimate improvement options implemented on the fleet. However, given the costs associated with each option, REHAB3 is preferred instead of full replacement. But at the same time, REPLACE generates more passenger miles in the long run, and thus may be more effective. Thus, as budgetary conditions improve and spending becomes more flexible, REHAB3 is replaced by the REPLACE option.

Fiscal considerations are also important in successful implementation of the programs. Given the budgetary constraints in the model, the proposed optimization framework can control costs through the planning period. Figure 4(a) compares the annual spending expected under various planning options, and the available budget, whereas Figure 4(b) illustrates the funding by type of bus based on capacity.



4(a) Annual spending compared to available budget

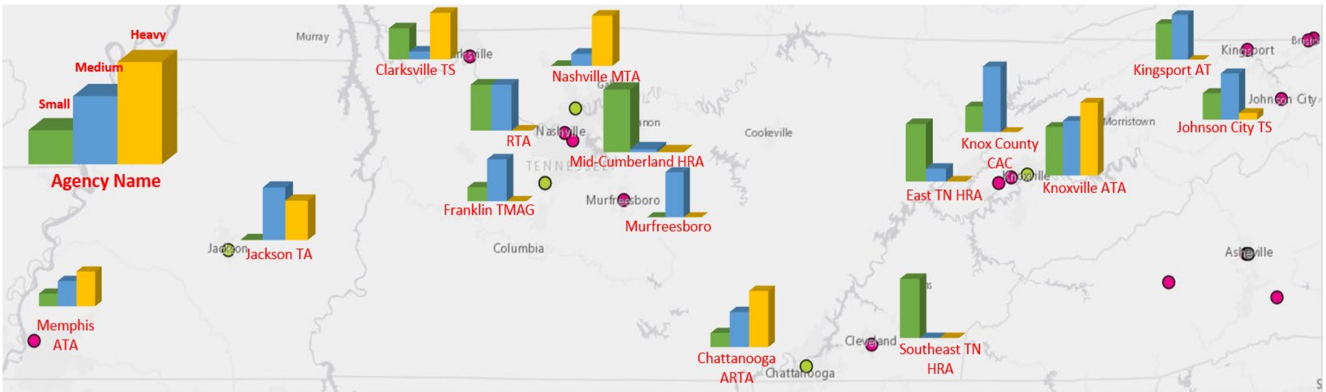


(b) Funding allocation by type of fleet for PSM and PSM-MNSL scenario

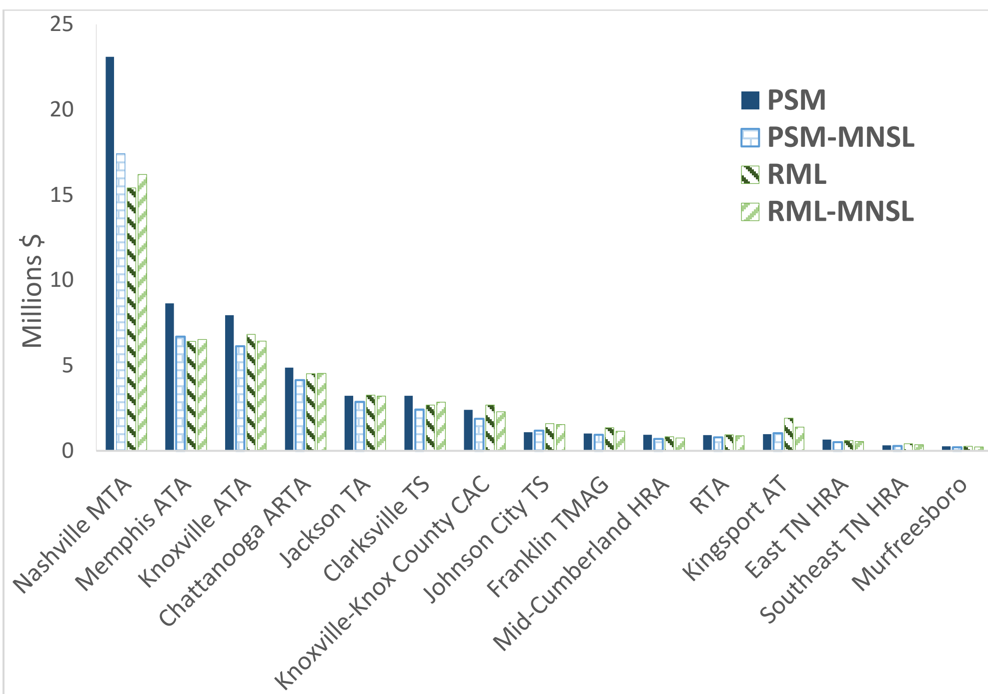
Fig. 4. Costs of implementing systemwide fleet improvement programs

In terms of annual spending under the two planning scenarios, the PSM-MNSL scenario requires much less initial funding as expected, since several buses may not be too close to their service life in the early planning period. However, in the second half of the period (2021 onwards specifically), the costs increase significantly and exceed the available budget. By the end of the ten-year period in 2025, the funding requirements are almost 50% higher than the available yearly budget of $5 million. It is thus likely to produce an environment of much financial uncertainty in the long term which may not be desirable. Spending under the PSM scenario, on the other hand, is relatively steadier and even aligns with the available budget in equilibrium in the outer years (2024 onwards). The heterogeneity of the fleet in terms of capacity also plays a role in funding allocation across the fleet. Also, it is observed that in the outer years, heavy buses witness a larger increase in the passenger miles compared to small and medium-sized buses, while at the same time the total proportion of funding allocated to them is also relatively higher.

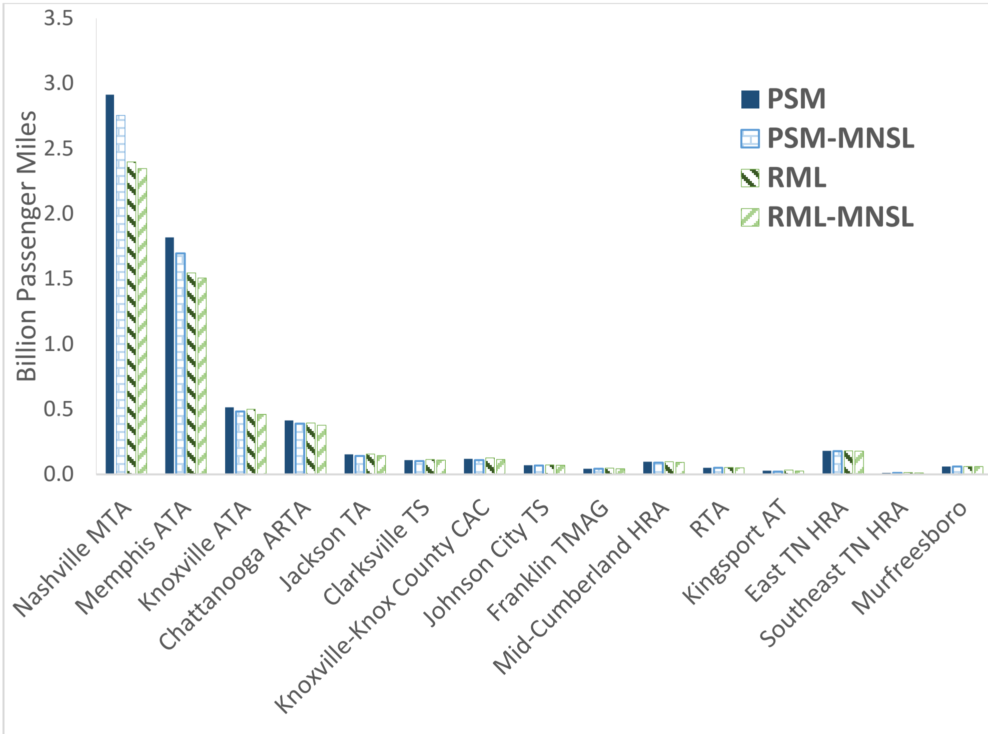
The following plots go into details about funding allocation at the individual agency level. As mentioned earlier, 15 transit agencies spread across Tennessee are considered in this analysis. Figure 5(a) shows their geographical locations, and the existing fleet composition (small, medium, and heavy buses) as illustrated in the legend insert in the top left portion of the figure. A diverse mix of buses is observed across agencies which captures the heterogeneity in fleet. Figure 5(b) reports the proportion of the total funding allocated to each of the 15 statewide transit agencies considered in this study, while Figure 5(c) shows the additional passenger miles traveled, distributed by agency.



5(a) Geographical locations and fleet composition of transit agencies



5(b) Planning period expenditure allocation by transit agency



5(c) Planning period passenger miles by transit agency

Fig. 5. Distribution of costs and benefits by agency through planning period (2016-2025).

It can be noted that the distribution of state funding across the 15 agencies considered in this study is driven by the prevalent condition of fleet in the agency and in proportion to the respective individual fleet size. More funds are directed to agencies operating a higher proportion of the total fleet. Also the benefits associated with the resource allocation in terms of additional mileage generated are proportional to the proportion of spending in each case.

Additional detailed results of the PSM scenario are presented in Table 3 below, including a distribution of remaining life across the fleet for each planning year, and the number of buses receiving each kind of improvement option (REHAB1, REHAB2, REHAB3, and REPLACE). Results on total annual spending per year expected in the future years and corresponding trends of the benefits gained in terms of PSM are also included. The last column indicates the proportion of fleet receiving some form of improvement treatment per year.

Table 3

Summary of PSM scenario results.

Year	Distribution of Remaining Life											Improvement Options				Annual Spending ($ mn)	TPSM (bn)	%Fleet Improved
	0	1	2	3	4	5	6	7	8	9	>=10	REHAB1	REHAB2	REHAB3	Replacement			
2016	38	21	24	41	47	34	25	16	7	0	1	31	39	36	5	$7.00	0.82	44%
2017	11	40	40	49	16	19	14	5	13	18	29	9	30	22	1	$4.62	0.82	24%
2018	24	36	39	14	20	22	15	21	29	15	19	5	9	41	4	$4.54	0.65	23%
2019	4	39	17	21	29	34	41	30	15	15	9	1	11	28	3	$4.02	1.05	17%
2020	6	16	20	26	40	43	58	18	15	6	6	3	3	1	44	$4.57	1.63	20%
2021	6	15	25	40	36	48	13	17	9	6	39	0	0	1	37	$4.99	1.38	15%
2022	10	21	30	29	46	13	13	10	8	6	68	0	0	0	34	$4.99	1.14	13%
2023	10	29	27	45	8	11	8	9	12	11	84	0	0	0	41	$5.00	1.09	16%
2024	19	23	34	6	9	7	8	14	14	22	98	0	0	0	35	$5.00	1.04	14%
2025	9	34	6	9	5	8	14	20	27	39	83	0	0	0	33	$5.00	1.97	13%

The total fleet size across all 15 agencies considered in this study is 254 as mentioned earlier. The annual spending is close to the available annual budget of $5 million in each year, where an average of about 30% of the total fleet receive some form of improvement per year. The proportion of fleet receiving improvement is higher in the earlier years and lower in the outer years after 2022 which is intuitive. Also, the number of buses undergoing the final replacement option is lower in the earlier years and higher in the later years, whereas inversely an opposite trend is observed across the other three rehabilitation-based options. This again makes intuitive sense because the rehabilitation options are relatively cheaper to implement and also add fewer years of life compared to the full replacement option, and hence may be more optimal to implement sooner rather than later. It is interesting to note that the number of buses with a remaining service life of more than or equal to 10 years increases gradually over the planning period, as they receive one or more forms of improvement over the years. This indicates that the suggested model and its optimization routine proceed as desired, and generate cumulative benefits over the years.

5. CONCLUSIONS

5.1. Summary of methodology and numerical findings

The model developed in this study provides a resource allocation framework across a mixed statewide fleet consisting of buses of various capacities and remaining life. Four types of fleet life improvement options (three levels of rehabilitation, and full replacement) are implemented among several constituent agencies over a planning period in an equitable manner, based on prevailing characteristics of their existing fleet.

Two scenarios are implemented to reflect different planning or policy objectives of agencies in real-life that may be driven by budgetary or other local constraints. The PSM and RML scenarios are more flexible where they allow for an improvement option to be implemented on buses at any stage of their service life, whereas under the corresponding Minimum Normal Service Life Based scenarios (PSM-MNSL, and RML-MNSL), a bus may be eligible to receive improvement only when it has reached the end of its service life. For both scenarios, an integer programming-based resource allocation model is developed with the objective of maximizing the PSM under several constraints including budgets, agency-specific policies regarding borrowing funds, etc. PSM reflects the benefits quantified in terms of additional passenger miles generated across the system over the coming years. A branch and bound algorithm is implemented to solve the large-sized optimization model (with more than 10,000 total decision variables), and a case-study of 15 transit agencies spread across Tennessee is presented. Both scenarios are compared to a 'do-nothing' scenario to articulate the benefits of setting up an optimal resource allocation framework over a simple fixed funding allocation.

Model results shows that PSM improves with the number of improvement options of each kind (REHAB1, REHAB2, REHAB3, and REPLACE) under various budget levels. Comparison between two planning objectives indicate that TPSMBA scenario may be more beneficial in the long-run compared to the MNSLBA scenario. Detailed results for the TPSMBA scenario illustrate merits of the proposed model, where it is evident that average remaining life of buses (or share of fleet with more than ten years of remaining service life) gradually rises towards the later years of the planning period (2016-2025).

5.2. Planning and policy implications

The case-study findings have several policy and planning contributions. Unlike previous studies in this domain where improvement options are applied individually for a specific year in the future for a single agency, the current model is more flexible where it can be applied over a temporally continuous planning horizon and across multiple agencies under the purview of a state agency. It is also multicriteria where size, budget and several policy constraints are considered. Transit agencies or state officials may utilize the framework for more effective and optimal asset management to enhance the service life and performance of their fleet, while implementing financially viable policies and improvement programs.

Based on the resource allocation framework presented in this study and the objectives and financial constraints specified therein, a transit agency's desired goal would be to invoke an improvement program that yields the largest supply-side benefits in terms of additional mileage or remaining fleet-life generated. In this regard, for the Tennessee case-study, model results (in Table 3) suggest that implementing cheaper and basic rehabilitation options of varying degrees (REHAB1, REHAB2, REHAB3) is more preferable in the earlier years, whereas more the expensive full replacement (REPLACE) option is more optimal in the outer years when a larger proportion of the fleet approaches the end of its service life and when other short-term rehabilitation options may not suffice. At the statewide level, allocation distribution illustrated in Table 3 and Figure 5 can be developed by the governing agencies to manage and assign funds among its constituent agencies through designated improvement programs over a planning horizon, to match desired quality/level-of-service requirements under prevalent budget conditions.

5.3. Future work

There are several future research avenues following the current work. The resource allocation framework presented here considers key two criteria— mileage and remaining life. However, it can be expanded to include emissions and air quality based criteria, which may be particularly relevant in light of the emphasis laid on environmentally sustainable urban transportation planning and programming. A more heterogenous fleet containing hybrid or low-emission buses, coupled with environmentally driven objectives and policies may lead to more diverse resource allocation outcomes. Along the same lines, the 'equity' component is not explicitly considered in this study where the total statewide funds are allocated more equitably among its agencies. The current set of results on funding allocation across agencies indicates a more uneven distribution of funds, mainly driven by fleet size and age of individual agencies.

Ultimately, additional supply-side operational variables such as mean distance to failure of buses may be incorporated into the modeling framework to make it more dynamic.

Although the current model is demonstrated on a Tennessee-based fleet comprising of small, medium, and large sized buses, it is transferable to other study areas where local agency-specific data can be acquired, most of which can be obtained from federal-level databases such as the NTD. The model can thus serve as a useful asset management tool for local and state agencies that intend to implement fiscal programs to preserve their aging fleet.

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