A SINGLE-STAGE GENETIC ALGORITHM MODEL FOR TRANSIT FLEET RESOURCE ALLOCATION

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ABSTRACT

In this paper, the authors present a single-stage optimization model that can be used to allocate limited resources among transit agencies for the purchase of new buses and for rehabilitation of the existing buses. The model is formulated as a non-linear optimization problem of minimizing the total weighted average remaining life of the fleet subject to the budgetary constraints. The constrained problem is transformed into an equivalent unconstrained one using the penalty function method and solved using genetic algorithm. The proposed model could act as a decision-support system for optimal resource allocation. This single-stage optimization model has a compact formulation, but requires large number of variables. The application of this decision support system is demonstrated through a case study utilizing actual fleet data from the Michigan Department of Transportation.

This proposed model is an extension of earlier work of the first author and his colleagues, on a two-stage sequential optimization model. The respective models are based upon linear optimization and the output from stage I serves as input to the stage II. The limitations of the two-stage model is that while local optimums may be attained by the respective models, a global optimum is not guaranteed. The proposed model presented in this paper is expected to deliver a global optimum.

A comparison of the results by the two models shows that while both approaches are viable, they result in different solutions suggesting multiple optimums, even though the same input data is used for both cases. The model needs to be expanded as a decision support system for several years. Further research is recommended to identify specific conditions under which one model may perform better than the other.

KEY WORDS

transit, resource allocation, linear programming, optimization, genetic algorithm, decision support system

INTRODUCTION

The addition of new buses to the existing fleet of any transit agency is a capital intensive process. In the US, the Federal Government provides a bulk of the capital funds needed to replace the aging transit fleet, with the requirement of a minimum matching support (usually 20%) from non-federal sources. The cost of replacing the aging transit fleet in the US to

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maintain current performance levels is estimated to exceed one billion dollars annually. Many state Departments of Transportation (DOT) that provide such matching funds to local agencies are duly concerned about the escalating costs of new busses.

Problem Statement

While the DOT's may not have enough capital funds to procure new buses for its constituent agencies, it may be possible for them to allocate capital funds *partly for the purchase of new buses, and partly for rehabilitation of existing buses*, and distribute the funds in an equitable manner. If one looks upon the statewide transit fleet as a major investment by the tax payers, the resolution of the above two questions would require the development of an asset management strategy. Unfortunately, very little research is reported in the literature on an efficient management strategy to allocate a fixed number of dollars to meet the fleet requirements by a combination of new and rebuilt buses.

Background Information

The combined fleet size of the transit agencies in Michigan is approximately 3,000 buses, with a net worth of at least $400 million. Every year, buses that complete their minimum normal service life (MNSL) requirement, become eligible for funds. However, because of budget constraints, only a portion of these buses are replaced. The MNSL for medium sized buses, the subject of this paper, as prescribed by federal guidelines is 320,000 km (200,000 miles) or 7 years of service. For the purpose of this paper, the following terms are adapted from the literature.

- <u>Replacement (REPL):</u> Process of retiring an existing vehicle and procuring a completely new vehicle. Buses replaced using federal dollars must have completed their MNSL requirements.
- <u>Rehabilitation (REHAB):</u> Process by which an existing bus is rebuilt to the original manufacturer's specification, with primary focus on the vehicle interior and mechanical system.
- <u>Remanufacturing (REMANF):</u> Process by which the structural integrity of the bus is restored to original design standards. This includes remanufacturing the bus body, the chassis, the drive train, and the vehicle interior and mechanical system.

Note in the remainder of this paper, the generic term 'Rebuild' has been used to mean Rehabilitate and/or Remanufacture.

FIRST GENERATION MODEL

Khasnabis et al developed a two-stage optimization model (termed as the First Generation Model) for resource allocation purposes with the following features.

- Annual allocation of capital dollars for the dual purpose of purchasing new buses and rebuilding existing buses, duly taking into account the 'maturation' process. (Stage 1)

- Annual distribution of capital dollars among the constituent agencies in an equitable manner. (Stage 2)

Stage 1 represents an optimization model where the objective is to maximize the weighted fleet life of the buses being replaced and rebuilt within the constraints of a fixed budget. The optimization algorithm used in stage 2 is based upon the premise that funds should be distributed among the constituent agencies that will maximize the sum total of the weighted average remaining life of the fleet of all the constituent agencies.

The two stage approach developed by Khasnabis et al is based upon linear optimization, and the output from stage 1 serves as an input to stage 2. While each of the two stages are directed toward local optimization, the solution may not necessarily reflect the global optimum. The First Generation Model has been reported in the literature.

SECOND GENERATION MODEL

In this paper, the authors present a single-stage optimization model, termed as the Second Generation Model that can be used to allocate resources among the constituent agencies directly for the replacement and/or rebuilding of existing buses. The model that uses a genetic algorithm based optimization for resource allocation can serve as a decision support system for state DOTs. Note, the Second Generation Model, unlike its predecessor, completely bypasses the intermediate step of allocating resources among new buses and rebuilt buses. Rather, it is a direct allocation process among the different program areas among the constituent agencies.

The Second Generation Model is formulated as a single stage optimization problem where the objective is to minimize the total weighted average remaining life (TWARL) for all the agencies. First the notations are introduced. Let x_{ik} is the number of buses by policy option k for agency i, r_{ij} is the distribution of remaining life of j for agency i, lk is the additional year added to the life of the bus due to the policy option k, ck is the cost of implementation of the policy option k, B is the total budge available for the project. The formulation of the problem is given as a mathematical program as below:

Program: I

$$Minimize: Z = \sum_i \frac{\sum_j (r_{ij} + x_{ik}) \times j}{\sum_j (r_{ij} + x_{ik})},$$

$$subjected\,to: \quad \sum_i \sum_k x_{ik} c_k \le B,$$

$$x_{ik} \ge 0.$$

The term x_{ik} is a binary decision variable which takes the form as below:

$$x_{ik} = \begin{cases} x_{ij} & if \;\; j = l_k, \\ 0 & otherwise. \end{cases}$$

The above optimization problem is large in terms of the number of variables and is solved using genetic algorithm. Since genetic algorithm is naturally suited for an unconstrained problem, the above constrained problem is converted to an equivalent unconstrained problem by an inner penalty method.

The genetic algorithm is a robust optimization algorithm suitable for large non-linear, non-convex, discontinuous, or non-structured problem. It is based on the principles of natural genetics in which complex information is stored and transferred by basic building blocks called genes. A simple implementation of the genetic algorithm first converts the real variables into binary codes using upper bound, lower bound, and the precision required for the variable. Then an instance of the solution is randomly generated for each variable and concatenated to for an individual. Similarly, a population of such individuals is generated and evaluated. The evaluation is done by finding the objective function value. For the current problem, the objective function is given by the equivalent unconstrained formulation of the program I. Based on the objective function value, three genetic operators, namely reproduction, cross-over, and mutation is applied to get better solution in the next generation. This process is repeated till convergence. Genetic algorithm is used primarily for the simplicity of the modeling.

RESULTS

The application of the two models (First Generation and Second Generation) is demonstrated through a comprehensive case study utilizing actual fleet data from the Michigan Department of Transportation (MDOT). The case study presented is for medium sized-medium duty buses for a total fleet size of 720 for 93 agencies that receive capital assistance from MDOT. The same strategy can be applied on a different subset of the agencies comprising specific peer groups, if necessary, or buses of a different size.

The fleet data used in this study is derived from the Public Transportation Management System (PTMS), developed by MDOT. Table 1 shows the distribution of the Remaining Life (RL) in years of the fleet for a few of the 93 agencies for the year 2002. A complete listing of the RL of all agencies is available in the project report. Since the MNSL of the buses are 7 years, a "7" year RL is indicative of new buses. Similarly, a "0" year RL would be indicative of those buses that have fulfilled their MNSL obligations, and hence are eligible for replacement. For the purpose of this demonstration, four possible program areas, replacement, and three levels of rebuilding, REHAB1, REHAB2 and REMANF, were used in the following feature:

REPL	Cost (Cmax) $81,540, expected life 7 years
REHAB1	Cost (Cmax) $17,800, extended life 2 years
REHAB2	Cost (Cmax) $24,500, extended life 3 years
REMANF	Cost (Cmax) $30,320, extended life 4 years

The last row of Table 1 shows that of the total fleet of 720, 235 buses have "0" year RL, (33%), needing immediate replacement. The Weighted Average Remaining Life (WARL) of this fleet, that has a range between 0 to 7 years, is 2.68 years, computed as the weighted average of the entire matrix. Smaller WARL's would be indicative of increasingly older fleet and vice-versa.

MDOT projected an available annual budget of \$5.79 million for the base year 2002, which is far short of the capital needed to replace all the 235 buses (\$19.17 million @ \$81,540 per bus). A prerequisite to the application of the two models is establishing an estimate of Cmax, the maximum investment that can be justified for the three program options REHAB1, REHAB2, and REMANF considered in the study. The procedure for estimating Cmax values developed by Khasnabis et al in an earlier study yielded the Cmax values stated above.

Results of First Generation Model

Application of the model resulted in a combination of 107 REHAB1 buses for 2 years of extended life, and 128 REMANF buses for 4 years of extended life with no new buses purchased in stage 1. The optimization problem was solved using the solver software. Further, this combination results in a weighted fleet life of 3.09 years for the 235 buses (representing the maximum of all possible combinations under the stated constraints), for a total investment of \$5.786 million. The reader is referred to the literature for detailed results.

Table 2 shows the distribution of the RL for a few sample agencies after the allocation of the resources for the year 2002 as an output from stage 2. Recall in stage 1, the model allocated 107 REHAB1 buses for 2 years and 128 REMANF buses for 4 years of extended lives. Table 2 shows that the total number of buses with 2 years of RL, have increased from 44 (Table 1) to 151 for an increase of 107, and buses with 4 years of RL have increased from 63 to 191 for an increase of 128 buses. Similarly, buses with "0" years of RL have been reduced from 235 in Table 1 to 0 in Table 2, further attesting to the fact that the needs of all the buses with "0" years of RL have been addressed by the model. All other columns in Table 2 remain unchanged compared to Table 1. Note that the allocation of the buses among the 93 agencies is made in such a manner that the grand total of the weighted lives of all agencies, TEWARL, i.e. $\sum_i \mathrm{EWARL}_i$, is maximized to 376.22 years (Table 2), compared to the value of 225.33 years prior to the assignment (Table 1). Similarly, the WARL value has increased from 2.68 years from Table 1 to 3.69 years in Table 2, indicating that the allocation has resulted in an increase of 1.01 years RL per bus. Also note that the total fleet size remains unchanged between Table 1 and 2.

Results of Proposed Second Generation Model

The solution of the second generation model is given in Table 3. The decision variables for the problem are denoted as x1, x2, x3, and x4 corresponding to management options namely REPL (X_1), REHAB1 (X_2), REHAB2 (X_3), and REMANF (X_4) and for all the 93 agencies. Therefore, the total decision variables for a year is 372 (93x4). Genetic algorithm provides their values at the end of the generations. For instance, the first row of the Table 3 shows the policy options for the first agency. Its option given by the optimization is x2=1, that is for one bus opt REHAB1. So the remaining life of that option is two years. The total fleet size of the first agency is three. The other two vehicles of that agency have remaining life 7 years and require no up gradation. Therefore, the cost of this option is 1x17800=17800. The existing weighted average remaining life (EWARL) is computed by the objective function of the Program I for i=1 is (1x2+2x7)/(1+2)=5.33. Similarly, the policy options and cost implication for all the agencies are shown in the Table 3. The last row of the table sums for all other agencies, that is the number of buses chosen for REPL, REHAB1, REHAB2, and REMANF are respectively 22, 189, 16, and 8 respectively. The total cost of this option is $5,792,618 which is slightly greater than the budget of $5,789,000 resulting in a deficit of $3,618. The table also shows the final objective function value which is the TEWARL, i.e. $\sum_i \mathrm{EWARL}_i$ as 393.46 (Table 3). The last row of the table also shows the distribution of the total remaining life of all the agencies.

Synthesis of Two Approaches

A comparative summary of the output from the two models is presented in Tables 4 and 5. Table 4 shows that both the models resulted in replacing 235 buses from the fleet by different combinations of vehicles. The First Generation Model results in a recommended investment of 107 vehicles to be rehabilitated for an extended life of 2 years and 128 vehicles to be remanufactured for an extended life of 4 years for a total investment of $5,785,560. The Second Generation Model results in a recommended investment of 22 new vehicles, and 189 and 16 rehabilitated vehicles for extended lives of 2 and 3 years respectively, and 8 remanufactured vehicles for an extended life of 4 years, for a total investment of $5,792,618.

The distribution of funds among the 93 agencies by the two methods, are already presented in Tables 2 and 3. Table 5 shows a summarized version of these two distributions by the RL-value of the bus fleet along with the base-year figures before assignment. The LP model attains a WARL value of 3.69 years and a TEWARL value of 376.72 years. The corresponding values by the GA model are 3.53 years and 393.46 years respectively

Table 1: 2002 Distribution of RL for a number of sample agencies for Medium Sized Buses before Allocation of Resources

Agency	Distribution of Remaining Life								Fleet Size	EWARLi(years)
	0	1	2	3	4	5	6	7		
1	1	0	0	0	0	0	0	2	3	4.67
2	1	0	0	0	0	0	0	0	1	0.00
3	1	0	0	0	0	0	0	0	1	0.00
4	0	0	0	0	3	3	0	1	7	4.86
5	4	0	0	2	4	2	0	1	13	3.00
6	1	0	0	0	1	6	0	1	9	4.70
7	1	0	0	0	2	1	1	0	5	3.80
8	2	0	0	0	0	0	1	0	3	0.00
9	2	0	0	0	0	0	0	0	2	0.00
10	18	4	0	0	0	0	0	0	22	0.18
11	3	0	0	0	0	0	0	0	3	0.00
. .	. .	. .	. .	. .	. .	. .	. .	. .	. .	. .
90	0	4	2	0	1	0	6	6	19	4.74
91	0	1	0	0	0	0	1	0	2	3.50
92	2	1	0	0	1	1	0	3	8	3.88
93	2	0	0	0	1	3	1	0	7	3.57
	235	122	44	23	63	77	78	78	720	225.23

Table 2: 2002 Distribution of number of RL for a number of sample agencies for Medium Sized Buses after Allocation of Resources

Agency	Distribution of Remaining Life								Fleet Size	EWARLi(years)	Additional New REHAB1 Buses	Additional New REMANF Buses
	0	1	2	3	4	5	6	7				
1	0	0	0	0	1	0	0	2	3	6.00	0	1
2	0	0	0	0	1	0	0	0	1	4.00	0	1
3	0	0	0	0	1	0	0	0	1	4.00	0	1
4	0	0	0	0	3	3	0	1	7	4.86	0	0
5	0	0	0	2	8	2	0	1	13	4.23	0	4
6	0	0	0	0	2	6	1	1	10	5.10	0	1
7	0	0	0	0	3	1	1	0	5	4.60	0	1
8	0	0	0	0	2	0	0	0	2	4.00	0	2
9	0	0	0	0	2	0	0	0	2	4.00	0	2
10	0	4	18	0	0	0	0	0	22	1.82	18	0
11	0	0	0	0	3	0	0	0	3	4.00	0	3
.	.	.	.	.	.	.	.	.	.	.	.	.
90	0	4	2	0	1	0	6	6	19	4.74	0	0
91	0	1	0	0	0	0	1	0	2	3.50	0	0
92	0	1	0	0	3	1	0	3	8	4.87	0	2
93	0	0	0	0	3	3	1	0	7	4.71	0	2
	0	122	151	23	191	77	78	78	720	376.72	107	128

Table 3: Results of the Second Generation Model

Agency	Distribution of remaining life (years)								Fleet Size	EWARLi (years)	Options				Total	Cost
	0	1	2	3	4	5	6	7			x1	x2	x3	x4	Nos	$
1	0	0	1	0	0	0	0	2	3	5.33	0	1	0	0	1	17800
2	0	0	0	0	0	0	0	1	1	7.00	1	0	0	0	1	81539
3	0	0	0	0	0	0	0	1	1	7.00	1	0	0	0	1	81539
4	0	0	0	0	3	3	0	1	7	4.86	0	0	0	0	0	0
5	0	0	4	2	4	2	0	1	13	3.62	0	4	0	0	4	71200
6	0	0	0	1	1	6	1	1	10	5.00	0	0	1	0	1	24500
7	0	0	1	0	2	1	1	0	5	4.20	0	1	0	0	1	17800
8	0	0	0	1	0	0	0	1	2	5.00	1	0	1	0	2	106039
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	…
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	…
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	…
86	0	40	49	0	2	0	4	0	95	1.79	0	47	0	0	47	836600
87	0	2	0	0	2	0	0	0	4	2.50	0	0	0	0	0	0
88	0	0	1	0	0	0	0	1	2	4.50	1	1	0	0	2	99339
89	0	0	0	2	0	5	0	2	9	5.00	0	0	0	0	0	0
90	0	4	2	0	1	0	6	6	19	4.74	0	0	0	0	0	0
91	0	1	0	0	0	0	1	0	2	3.50	0	0	0	0	0	0
92	0	1	2	0	1	1	0	3	8	4.38	0	2	0	0	2	35600
93	0	0	2	0	1	3	1	0	7	4.14	0	2	0	0	2	35600
Total	0	122	233	39	71	77	78	100	720	393.46	22	189	16	8	235	5792618

Table 4: Comparison of the Resource Allocation Output by the Two Models

Model	Assignment of Resource in the Program Areas				Total Number of Buses	Amount Spent ($)	Budget ($)
	X_1 @ $81,540 (7 yrs)	X_2 @ $17,800 (2 yrs)	X_3 @ $24,500 (3 yrs)	X_4 @ $30,320 (4 yrs)			
First Generation	0	107	0	128	235	5,785,566	5,789,000
Second Generation	22	189	16	8	235	5,792,618	5,789,000

Table 5: Comparison of RL Distribution by the Two Models

Model	Distribution of Remaining Life (yrs)									WARL (yrs)	TEWARL (yrs)
	0	1	2	3	4	5	6	7	Total		
Base Year (2002) Prior to Assignment	235	122	44	23	63	77	78	78	720	2.68	225.23
First Generation	0	122	151	23	191	77	78	78	720	3.69	376.72
Second Generation	0	122	233	39	71	77	78	100	720	3.53	393.46

CONCLUSION

In summary, the GA model requires a slightly higher investment (approximately $7000), attains a slightly lower WARL value (by 0.16 years), but a slightly higher TWARL-value the object of maximization (17 years). Further testing of the GA model output is needed before one can conclude if the GA model indeed attains the global optimum, as it is expected to do. The TEWARL value of 393.46 years by the GA model is indeed higher than the corresponding value of 376.72 years attained by the LP model. But whether or not, the number of 393.46 years is the highest attainable value for this specific case is a matter of future research.

The major contribution of this study is the development of a unified methodology for the determining which all agencies need the investment at the same time deciding the policy options for each agency. Although this study demonstrated the management strategy for one year, the methodology could be extended over number of years enabling the agency to formulate strategy for long-term implementation. Genetic algorithm could be used in this context in spite of the explosion of variables and complex formulation.

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