A SINGLE-STAGE MIXED INTEGER PROGRAMMING 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 maximizing the total weighted average remaining life of the fleet subject to budgetary and other constraints. The constrained problem is transformed into an equivalent unconstrained one using the penalty function method and solved using mixed integer programming (MIP). 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 transit 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 method. The respective models are solved by linear programming (LP) and the output from stage I serves as input to the stage II. The limitation of the two-stage model is that while local optima may be attained by the respective models, a global optimum is not guaranteed. The 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 optima, even though the same input data is used for both cases. The model needs to be expanded as a decision support system for resource allocation over multiple years. Further research is recommended to identify specific conditions under which one model may perform better than the other.

Keywords: transit, resource allocation, linear programming, optimization, mixed integer programming, 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 maintain current performance levels is estimated to exceed one billion dollars annually *(1)*. 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 state 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 to 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 questions of allocation and distribution 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 scarce resources 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, as specified by the Federal Government, 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.

- Replacement (REPL): Process of retiring an existing vehicle and procuring a completely new vehicle. Buses replaced using federal dollars must have completed their MNSL requirements.
- Rehabilitation (REHAB): Process by which an existing bus is rebuilt to the original manufacturer's specification, with primary focus on the vehicle interior and mechanical system.
- Remanufacturing (REMANF): 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 REHAB and/or REMANF.

LITERATURE REVIEW

A brief literature review on three relevant topics: REHAB/REMANF, Transit Asset Management and Use of Optimization in Transit is presented below. A more complete review was presented by Khasnabis et al. in an earlier TRB paper *(2)*.

REHAB and REMANF Issues

The topics of REPL, REHAB, and REMANF practices and polices received significant research attention in the 1980s and renewed research interest in the late 1990s *(3–6)*. The literature review clearly showed that remanufacturing and rehabilitating buses, if done properly, can be a cost-effective option. Little research is reported on allocation of capital funds for the dual purpose of REPL, and REBUILD of the existing buses.

Asset Management Issues

Asset management concepts have been used in the transportation field with varying degrees of success. Asset management is defined as a “systematic process of operating, maintaining, and upgrading physical assets cost-effectively. It combines engineering and mathematical analyses with sound business practice and economic theory” *(7)*. Management systems have been applied to pavement, rebuilding infrastructures, human resources, bridges, traffic, and safety *(8, 9)*. Very little research, other than the work by Berrang et al. *(9)*, is reported in the literature on asset management involving transit properties.

Use of Optimization Tools in Transit

Mathematical programming has been used for the allocation of limited resources, primarily in the defense industry. The problem usually involves the maximization or minimization of an objective function comprising a set of variables called decision variables *(10, 11)*. The variables are then subject to various constraints, expressed in the form of inequalities or equalities. Different optimization techniques exist, such as linear programming (LP), integer programming, nonlinear programming, and dynamic programming *(12)*. The review of the transit literature indicates that the use of optimization techniques in transit fleet management has been very limited, even though optimization has been used successfully in computer aided scheduling and dispatching support tools for transit operation.

FIRST GENERATION MODEL

As a part of the USDOT study, Khasnabis et al. developed a two-stage optimization model (termed as the First Generation Model) with two sub-models, one for each stage as described below *(13)*.

- 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. This research was conducted by Khasnabis et al. at Wayne State University during 2002-2003, with funding provided by the US DOT through the University Transportation Center Program at the University of Wisconsin, Madison *(13-15)*. The structure of the two stage model is presented in detail in an earlier TRB paper, and is not reported here for brevity *(16)*. The Second Generation Model reported in this paper builds upon the knowledge generated in the development of the earlier work.

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. Research on the Second Generation Model was initiated in 2004 while the principal author served as a visiting faculty at the Indian Institute of Technology Bombay, India, as a Fulbright research scholar. The impetus for this work was the perception that the First Generation Model, while it achieved local optimum at each of the two stages, may not have achieved global optimum. The Second Generation model uses a mixed integer programming based optimization for resource allocation and 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. Thus there are two major differences between the two models, namely in structure (Two-Stage vs Single-Stage) and in the solution methodology (Linear Programming (LP) vs Mixed Integer Programming (MIP)). An earlier effort by Khasnabis and Mathew to develop a single stage model using Genetic Algorithm showed little difference in the results *(17)*.

Formulation:

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} :*the number of buses by policy option k for agency i*

r_{ij} :*the distribution of remaining life of j for agency i*

l_k :*the additional year added to the life of the bus due to the policy option k*

y_{ik} :*the number of buses with policy option k adopted for agency i*

c_k :*the cost of implementation of the policy option k*

B :*the total budget available for the project*

A :*the total number agencies*

Y :*the service life of buses*

The formulation of the problem is given as a mathematical program as below:

$$Maximize: \ Z = \sum_{i=1}^{A} \frac{\sum_{j=1}^{Y} (r_{ij} + x_{ij}) \times j}{\sum_{j=1}^{7} r_{ij} + x_{ij}} \tag{1}$$

subjected to:

$$\sum_i \sum_k y_{ik} c_k \le B \tag{2}$$

$$\sum_k y_{ik} = r_{i0} \tag{3}$$

$$\sum_k y_{ik} = r_{i0} \tag{4}$$

where

$$x_{ij} = \begin{cases} y_{ik} & if \ j = l_k, l_k \in \{2,3,4,7\} \\ 0 & Otherwise \end{cases} \tag{5}$$

Other notations used in the paper are:

$WARL = Weighted\ Average\ Remaining\ Life\ of\ the\ entire\ fleet$

$EWARL_i = Existing\ Weighted\ Average\ Remaining\ Life\ of\ fleet\ for\ agency\ i$

$TEWARL = Sum\ Total\ of\ the\ EWARL's\ of\ fleet\ for\ all\ agencies = \sum_i EWARL_i$

$NWARL_i = New\ Weighted\ Remaining\ Life\ fleet\ of\ for\ agency\ i$

$TNWARL\ _i = Sum\ Total\ of\ NWARL_i\ of\ fleet\ for\ all\ agencies = \sum_i NWARL_i$

The objective function (1) is the sum total of the weighted average remaining life of the fleet of all the constituent agencies. The equation (2) gives the budget constraint. The Constraint specified in equation (3) ensures that all the buses that have completed their MNSL requirements will be either remodified or replaced. Equation (4) is a non-negativity constraint, which makes sure that the options chosen for improvement of buses of zero service life are never negative. Equation (5) is a definitional constraint. According to this constraint, life of the buses are improved by either 2, 3, 4, or 7 years for the remodified bus. Other buses in the system will have no additional years added. As explained later in the document, the REBUILD option extends the life of the bus by two, three and four years, while the REPL option provides a new bus with seven years of expected life. Hence the value of y_{ik} can be 2, 3, 4 or 7 years

Implementation:

The above optimization problem is large in terms of the number of variables and is solved using Generalized Reduced Gradient (GRG) Solver *(18)*. Branch and Bound method was used to deal with integer variables and constraints, which increases the chances to find an optimal solution. "Branch and Bound" and "Branch and Cut" strategies help to cut down on this exponential growth and to reduce the operation time for mixed-integer programming (MIP). The Branch & Bound method begins by finding the optimal solution to the relaxation of the integer problem, ignoring the integer constraints. If the decision variables with integer constraints already have integer solutions, no further work is required. If one or more integer variables have non-integer solutions, the Branch & Bound method chooses one such variable and creates two new sub problems where the value of that variable is more tightly constrained. These sub problems are solved and the process is repeated, until a solution is found where all of the integer variables have integer values (to within a small tolerance) *(12, 19)*.

Cut generation derives from so-called cutting plane methods that were among the earliest methods applied to integer programming problems, but they combine the advantages of these methods with the Branch & Bound method to yield a highly effective approach, often referred to as a Branch & Cut Algorithm. A cut is an automatically generated linear constraint for the problem, in addition to the constraints specified. Cut generation enables the overall Branch & Cut algorithm to more quickly discover integer solutions, and to eliminate branches that cannot lead to better solutions than the best one already known. Branch & Bound algorithm can guarantee that a solution is optimal or is within a given percentage of the optimal solution. GRG nonlinear Solver is augmented with "multistart" and "clustering" methods for global optimization *(18)*. It can be automatically run many times from judiciously chosen starting points, and the best solution found will be returned as the optimal solution.

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 same database used in the First Generation model was used in the Second Generation model to permit a direct comparison of results. Hence the First Generation model results are adapted from the original report *(13)*. Results of the Second Generation model represent the most recent work by the authors. 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 base year 2002. A complete listing of the RL of all agencies is available in the project report. Since the MNSL of the buses are seven years, a "seven" year RL is indicative of new buses. Similarly, a "zero" 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 "zero" year RL, (33%), needing immediate replacement. The Weighted Average Remaining Life (WARL) of this fleet, that has a range between 0 (all buses needing replacement) to seven (all new buses) 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 *(20)*. The Microsoft Excel Solver Program was used for the First Generation Model *(21)*.

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 four years of extended life with no new buses purchased in stage I. 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 (stage-1 output). The reader is referred to the literature for detailed results *(2, 13, and 16)*.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 II. Recall in stage I, the model allocated 107 REHAB1 buses for two years and 128 REMANF buses for four 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 (Table 2) for an increase of 107, and buses with four 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 one to zero in Table 2, further attesting to the fact that the needs of all the buses with "zero" 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, TNWARL, i.e. $\sum_i NWARL_i$, 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 four program areas namely REPL (X_1), REHAB1 (X_2), REHAB2 (X_3), and REMANF (X_4) and for all the 93 agencies. Therefore, the total decision variable for a year is 372 (93x4). The Second Generation Model provides their values at the end of the model run. For instance, the first row of the Table 3 shows the fleet assigned to a different program area for the first agency. It shows that one bus has been assigned to the X_4 category (REMANF) for a RL of four years. The total fleet size of the first agency is three. The other two vehicles of that agency have remaining life seven years and require no up-gradation. Therefore, the cost of this option is 1 x 30,320=30, 320. The NWARL is computed by the objective function of the Program I for i=1 is (1x4 +2x7)/(1+2)=6.0. Similarly, the program areas 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 18, 180, 1, and 36 respectively. The total cost of this option is $5,787,740 which is $1,260 less than the budget of $5,789,000. Table 3 also shows the final objective function value which is the TNWARL, i.e. $\sum_i NWARL_i$ as 409.07. 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 18 new vehicles, and 180 and 1 rehabilitated vehicles for extended lives of two and three years respectively, and 36 remanufactured vehicles for an extended life of 4 years, for a total investment of $5,787,740.

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 First Generation model attains a WARL value of 3.69 years and a

TNWARL value of 376.72 years. The corresponding values by the Second Generation Model are 3.56 years and 409.07 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
Total	**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**	**NWARLi (years)**	**Options**		**Total Nos.**	**Cost ($)**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**			**X_2 (2 yrs)**	**X_4 (4 yrs)**		
1	0	0	0	0	1	0	0	2	3	6	0	1	1	30320
2	0	0	0	0	1	0	0	0	1	4	0	1	1	30320
3	0	0	0	0	1	0	0	0	1	4	0	1	1	30320
4	0	0	0	0	3	3	0	1	7	4.86	0	0	0	0
5	0	0	0	2	8	2	0	1	13	4.23	0	4	4	121280
6	0	0	0	0	2	6	1	1	10	5.1	0	1	1	30320
7	0	0	0	0	3	1	1	0	5	4.6	0	1	1	30320
8	0	0	0	0	2	0	0	0	2	4	0	2	2	60640
9	0	0	0	0	2	0	0	0	2	4	0	2	2	60640
10	0	4	18	0	0	0	0	0	22	1.82	18	0	18	320400
11	0	0	0	0	3	0	0	0	3	4	0	3	3	90960
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
90	0	4	2	0	1	0	6	6	19	4.74	0	0	0	0
91	0	1	0	0	0	0	1	0	2	3.5	0	0	0	0
92	0	1	0	0	3	1	0	3	8	4.87	0	2	2	60640
93	0	0	0	0	3	3	1	0	7	4.71	0	2	2	60640
Total	**0**	**122**	**151**	**23**	**191**	**77**	**78**	**78**	**720**	**376.72**	**107**	**128**	**235**	**5,785,560**

WARL=3.69 years/bus, TNWARL=376.72 years

TABLE 3 Results of the Second Generation Model

Agency	Distribution of remaining life (years)								Fleet Size	NWARLi (years)	Options				Total Nos	Cost ($)
	0	1	2	3	4	5	6	7			X_1 (7yrs)	X_2 (2yrs)	X_3 (3yrs)	X_4 (4yrs)		
1	0	0	0	0	1	0	0	2	3	6.00	0	0	0	1	1	30320
2	0	0	0	0	0	0	0	1	1	7.00	1	0	0	0	1	81540
3	0	0	0	0	0	0	0	1	1	7.00	1	0	0	0	1	81540
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	1	0	1	6	1	1	10	4.90	0	1	0	0	1	17800
7	0	0	0	0	3	1	1	0	5	4.60	0	0	0	1	1	30320
8	0	0	0	0	1	0	0	1	2	5.50	1	0	0	1	2	111860
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..	..
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	0	0	2	0	0	0	2	4.00	0	0	0	2	2	60640
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**	**224**	**24**	**99**	**77**	**78**	**96**	**720**	**409.07**	**18**	**180**	**1**	**36**	**235**	**5,787,740**

WARL= 3.56 years/bus, TNWARL=409.07 years

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 ($)	Budget ($)	Weighted Fleet Life[1]
	X1 @ \$81,540 (7 yrs)	X2 @ \$17,800 (2 yrs)	X3 @ \$24,500 (3 yrs)	X4 @ \$30,320 (4 yrs)				
First Generation	0	107	0	128	235	5,785,566	5,789,000	309
Second Generation	18	180	1	36	235	5,787,740	5,789,000	NA

[1] Weighted Fleet Life of Buses being replaced, rehabilitated and remanufactured (Stage-1 output)

TABLE 5 Comparison of RL Distribution by the Two Models

Model	**Distribution of Remaining Life (yrs)**									**WARL (yrs)**	**TWARL (yrs)**	**TNWARL (yrs)**
	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**Total**			
Base Year (2002)	235	122	44	23	63	77	78	78	720	2.68	225.23	
Prior to Assignment												
First Generation	0	122	151	23	191	77	78	78	720	3.69		376.72
Second Generation	0	122	224	24	99	77	78	96	720	3.56		409.07

CONCLUSION

As indicated earlier, the Second Generation Model was initiated as a collaborative work between the first two authors from two institutions to explore the issue of local vs global optimum. The Second Generation Model resulted in higher TNWARL, the object of optimization (409.07 vs 376.72) and slightly lower WARL value (3.56 vs 3.69) attained by MIP compared to the First Generation Model results attained by LP. In both cases the investment needed was within the budget, being \$5.785 million and \$5.787 million for the LP and MIP models respectively, against an allocated budget of \$5.789 million. It appears that the Second Generation model attained a global maximum and all constraints are satisfied and the model converged to the reported value after 1000 iterations. Whether or not the solution attained the global optimum cannot be guaranteed without additional tests.

One can conclude that both the First Generation and Second Generation model are viable. On a macroscopic basis (TNWARL, WARL, etc.), little difference is observed between the results so far, although on a microscopic basis (distribution of fleet among constituent agencies by RL), there are significant differences. Intuitively, the Second Generation Model appears more robust because of its single-stage structure making the attainment of the global maximum more feasible.

The major contribution of this study is the development of a unified methodology for the determining the budget investment strategy under the framework of program option specified. This study demonstrated the strategy for one year, and thus represents only a framework for analysis. Further research is needed to extend the methodology to a minimum of seven years representing the MNSL enabling the agency to formulate strategy for long-term implementation. Genetic algorithm could be explored in this context in spite of the explosion of variables and complex formulation *(17, 19, and 22)*.

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