Equipment Replacement Decision Making: Challenges and Opportunities

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ABSTRACT: A primary objective for equipment managers is to replace the right equipment at the right time and at the lowest overall cost. To help accomplish this task, a theoretically sound and practically feasible equipment replacement optimization methodology has been developed so that a significant amount of money can potentially be saved. In this paper, the challenges and opportunities associated with equipment replacement decision making are discussed in detail. First, a comprehensive review of the state-of-the art and state-of-the practice literature on the equipment replacement optimization (ERO) problem is conducted. Second, the developed ERO software components and functionalities are presented. Third, several challenges faced by the research team during the ERO software development process are described including statistical modeling (purchase cost forecasting and down time cost estimating), optimization (in terms of stochastic dynamic programming (SDP) and ERO under budget constraints), and software implementation (particularly for the SDP approach) challenges. Detailed information as to how such challenges have been overcome and turned into opportunities using the current Texas Department of Transportation (TxDOT) data is also presented. Fourth, real opportunities and the promising future for ERO decision making tools are discussed and supported by comprehensive numerical results and their implications. Finally, a summary of the information presented and details about future research directions are also given.
1. INTRODUCTION

As assets age, they generally deteriorate, resulting in rising operating and maintenance (O&M) costs and decreasing salvage values. Furthermore, newer assets that are more efficient and better at retaining their value may exist in the marketplace and be available for replacement. The conditions of deterioration and technological changes motivate public and private agencies that maintain fleets of vehicles and/or specialized equipment to periodically replace vehicles composing their fleet. This decision is usually based upon a desire to minimize the total or expected fleet costs, which typically include the acquisition, O&M cost, and salvage value over a definite or infinite horizon (1).

The equipment replacement optimization (ERO) effort is also extremely important in the context of overall fleet management efforts. The best equipment replacement decision tool in the world may not be that useful if there is no funding available to purchase new vehicles for the replacement of old ones. An ERO decision tool, if well-developed, can be effectively used as part of a long-range fleet replacement plan and to assist in estimating the budget required to meet future replacement needs (1).

A primary objective for equipment managers is to replace the right equipment at the right time and at the lowest overall cost. To help accomplish this task, a theoretically sound and practically feasible equipment replacement optimization methodology can be implemented so that a significant amount of money can potentially be saved.

Much research has been undertaken in general ERO area without using real-world fleet cost data. A detailed review of the state-of-the art and state-of-the practice literature of the ERO problem and commercial fleet management systems currently available worldwide can be seen and examined in a separate research paper (1). In summary, previous research efforts, which have been made to examine the ERO problem, can be classified into and solved using three categories from the solution approach perspectives:

1) Minimum Equivalent Annual Cost (EAC) Approach

The most basic ERO problem is studied under the assumption of no technological change over an infinite horizon (i.e., the equipment is needed indefinitely). The “no technological change” is sometimes also referred to as “stationary cost” by some researchers in the sense that an asset is replaced with the purchase of a new, identical asset with the same cost. Under this assumption, the optimal solution to the infinite-horizon equipment replacement problem with stationary costs is to continually replace an asset at the end of its economic life. Once determined, the asset should be continuously replaced at this age under the assumption of repeatability and stationary costs (1). Weissmann et al. (2) provides a typical example of those that use the minimum EAC approach to solving the ERO problem.

2) Experience/Rule Based Approach

Many state DOTs use the experience/rule based approach to make keep/replacement decisions for their equipment, particularly during the early stages of ERO implementation (1). For example, TxDOT uses threshold values for age, use of an equipment unit, and repair cost as inputs for replacement (1, 3). This experience/rule based approach to the ERO problem can work really well for the fleet manager under certain circumstances. However, this approach heavily depends upon the fleet manager’s judgment and experience with the ERO. In particular, detailed
information about the rules currently used by TxDOT for determining the replacement time for many classcodes/equipment units can be found on the TERM website (3).

3) Dynamic Programming (DP) Approach

The solution of continuously replacing an asset at the end of its economic life based on the minimum EAC method is optimal only under the assumptions of an infinite horizon and stationary costs. However, many situations occur in practice in which an asset is required for a finite length of service (i.e., finite horizon). In particular, if the costs (including O&M cost and salvage value) are age based, assuming constant or predetermined utilization over a finite horizon, the DP approach is commonly used to solve the ERO problem.

There has been an enormous amount of research regarding ERO with a finite time horizon using the deterministic dynamic programming (DDP) approach (4, 5, 6, 7, 8, 9, 10, 11). When using the DDP approach, both the vehicle usage and the annual O&M cost are assumed to be constant or predetermined. However, due to randomness in real operations, these expected equipment utilisations and subsequent costs are not normally realized in practice, thus invalidating the replacement optimization decisions to some degree. In this regard, the stochastic dynamic programming (SDP) approach may be the preferred approach for solving the ERO problem because it can explicitly consider the uncertainty in the vehicle utilization and the annual O&M costs accordingly. Such examples of SDP-based ERO research efforts can be found in several papers (8, 12, 13, 14). In particular, Hartman (14) examined the effect of probabilistic asset utilization on replacement decisions through the use of DP, in which states were defined by the asset's age and cumulative utilization at each stage and the solution was determined by minimizing the expected cost.

Although previous research efforts have provided a solid basis for ERO, none of them used real-world fleet cost/usage data, and all previous case studies are limited by small samples. As a result, many underlying issues, including both challenges and opportunities, involved in the ERO process have yet to be identified and explored.

To the best of our knowledge, the ERO solution software developed, and to be discussed in this paper, is the first of its kind to be targeted at a real-world application (using available fleet data) (15, 16, 17, 18). According to the Texas Department of Transportation (TxDOT) (2), the department owns and maintains an active fleet of approximately 17,000 units and TxDOT annually disposes of approximately ten percent of its fleet. In terms of monetary value, TxDOT has a fleet valued at approximately $500,000,000, with an annual turnover of about $50,000,000. Undoubtedly, any methodology that can help improve TxDOT’s replacement procedures can potentially save millions of dollars. Since September 1, 2009, TxDOT has been sponsoring The University of Texas at Tyler (UT Tyler) and The University of Texas at Austin (UT Austin) through two research projects, namely project 0-6412 “Equipment Replacement Optimization” (spanned September 1 2009 – August 31, 2011) and (ongoing) project 0-6693 “Equipment Replacement/Retention Decision Making” (from September 1, 2011 to present). As a result of these two TxDOT projects, a comprehensive DP-based optimization solution methodology has been developed to solve the ERO problem using TxDOT’s current fleet data (15, 16, 17, 18). The developed ERO software components and functionalities will be presented in detail in section 2.
In particular, it should be noted that during the process of developing the ERO software for TxDOT, the research team has encountered and overcome many challenges, which can be classified into three categories: statistical modeling (including purchase cost forecasting and down time cost estimating), optimization (in terms of the SDP modeling and ERO under budget constraints), as well as software implementation (particularly for the SDP approach). As part of the software’s development, these challenges have been met and, in the process, turned into opportunities. Preliminary testing has shown that a significant amount of money can be saved annually by TxDOT using the developed ERO software (1, 15, 16, 17). The purpose of this paper is to discuss in detail the challenges and opportunities associated with the developed ERO software and the ERO problem itself, in general, so that it can provide some useful information for any future software development and research directions.

The subsequent sections of this paper are organized as follows: Section 2 describes the developed ERO software components and functionalities. Section 3 presents several challenges (including the three aspects of statistical modeling, optimization and software implementation) faced by the research team during the ERO software development process and how such challenges have been overcome and turned into opportunities using the current TxDOT data. Section 4 discusses the real opportunities and promising future for the ERO software, supported by comprehensive numerical results and their implications. Finally, a summary of the information presented and details about future research directions are also given.

2. ERO SOFTWARE COMPONENTS AND FUNCTIONALITIES

This section describes the developed ERO software components and functionalities in detail.

2.1. ERO Software Components

As shown in Figure 1, the ERO software developed as a result of the TxDOT projects consists of three main components (1, 15, 16, 17): 1) A SAS Macro based Data Cleaner and Analyzer, which undertakes the tasks of raw data reading, cleaning and analyzing, as well as cost estimation and forecasting; 2) A DP-based optimization engine (including both DDP and SDP) that minimizes the total cost over a defined time horizon; and 3) A Java-based Graphical User Interface (GUI) that takes parameters input by users and coordinates the Optimization Engine and SAS Macro Data Cleaner and Analyzer. As one can see from previous research efforts (1, 15, 16, 17), the equipment purchase cost model is year-based, the annual O&M cost is both equipment age- and mileage-based, and the salvage values are dependent upon both the model year and equipment age. All of this data comes from SAS as outputs of the SAS macro based data cleaner and analyzer and act as inputs to the DP-based optimization engine. Solving the ERO problem using the DP approach requires all costs (such as annual O&M costs including all repairs, regular maintenance and down time penalty costs, and salvage values, as well as purchase costs of the new model year) to be minimized. Both Bellman and Wagner formulations are used and implemented as the DP solution approach to solving the ERO problem (1, 15, 16, 17).

2.2. ERO Software Functionalities
Foremost, the developed ERO software allows the user to select two separate approaches to tackle the ERO problem (17): 1) “Current Trend” approach, which takes all the information from current Texas Equipment Replacement Model (TERM) data that are “error- and outlier- free” and assumes that the same utilization and subsequent O&M cost trends will continue for all future years. For example, the current TERM data shows that equipment utilization generally decreases as equipment ages and therefore it assumes this trend will continue into the future; and 2) “Equal Utilization” approach, which takes the average mileage across all equipment units with same classcode and assigns this number as the utilization for those equipment units during that year. Note that year-to-year utilization for the same classcode can still be different under this assumption.
Many other functions have also been incorporated in the developed ERO software including the following (17): 1) The software allows the user to specify budget constraints, as well as the time horizon that the program will use during optimization. 2) The software allows users to selectively “Clean the data”; to remove outliers or choose to leave outliers in the data and create EXCEL outputs for review. 3) The user can choose to run the software using automatically generated cost data from SAS or the Editable cost data that they have updated manually, at the beginning of each year. 4) The user can choose from several different approaches, namely: Cost Current Trend or Cost Equal Mileage (Utilization); DDP or SDP, and Bellman or Wagner approaches. 5) The user can also choose to delay the replacement of equipment or replace it early by specifying a positive or negative delay time. 6) The software can also run optimization on a single used piece of equipment from a specific classcode, on all equipment units from either one specific classcode or from all classcodes, or on brand new equipment units from either one specific classcode or from all classcodes; for a specific TxDOT district or all districts. 7) The software provides an EXCEL report for the cost savings by comparing the optimal solution with the benchmark rules result (prior replacement approach), and it provides an EXCEL report summarizing the cost savings by comparing the optimal solution with the “delay by \( N \) years” option or the “ignore the optimized decision” option. 8) Finally, users can add new annual TERM data as it becomes available and make dynamic keep/replacement decisions for any chosen classcode or equipment unit (1, 15, 16, 17).

3. CHALLENGES

This section presents several challenges (including the three aspects of statistical modeling, optimization and software implementation) faced by the research team during the ERO software development process. It specifically details challenges encountered during development of purchase cost and down time cost forecasts, along with implementation of SDP solution methodology and optimization using budget constraints.

3.1. Statistical Modeling Challenges

3.1.1. Purchase Cost Forecasting

The original strategy for forecasting the purchase cost for the ERO decision process depended on the use of SAS, as initiated by the GUI, to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast the equipment purchase cost versus model year. In particular, the SAS macro source codes were developed for the following five different types of models: 1) Linear; 2) Polynomial; 3) Logarithm; 4) Exponential; and 5) Power.

The SAS macro also had the capability of running through all of the linear and nonlinear models and automatically identifying and selecting the best-fit model, per the highest R-square value, for forecasting the equipment purchase cost (using model year) for any chosen classcode. The objective was to use SAS to create and select the best-fit model for the data and incorporate that model for forecasting purchase cost into the optimization engine (1, 15).
Through the evaluation of early versions of the software, it was discovered that the purchase cost forecasts for a number of the classcodes was unduly influencing the keep/replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that yielded decreasing, and in some cases negative, purchase costs for future years. The evaluation of the quality of the fit (R-square value) for the model options led to the software program choosing non-linear models for many of the equipment classcodes. Due to the distribution of data for some of these equipment types, this resulted in a curvilinear model with a negative slope generated over the years near the end of the recorded history of purchase costs (notably due to more recent economic conditions), as illustrated in Figure 2.

Figure 2 shows the nonlinear model yielding a good fit for the data (R-square value of 0.7988); however, the slope of the model is negative at the end of the existing time period and would subsequently result in a decreasing forecasted purchase cost for future years. Therefore, the ERO software using models like this one resulted in purchase costs being forecasted to decrease each year of the time horizon. The decreasing trend was speculated to be a result of a short-term decline in purchase costs brought on by the recession. While this represents a real phenomenon, it does not justify a sustained decrease in forecasted purchase costs over a 20-year horizon, as evidenced by the subsequent increase in cost in more recent years. It was determined that the negative slope generated by the curvilinear model would have a detrimental impact on the ability of the optimization engine to appropriately generate recommendations for replacing equipment. As such, several methods of troubleshooting the problem were identified and tested.

To evaluate the effectiveness of each of the methods attempted to correct the problem, classcode 430070, for light-duty trucks, was chosen for further evaluation. The methods identified for improving purchase cost forecasting included implementation of a factor of the inflation rate
(multiplied by the purchase cost) in place of a statistical model, use of the manufacturer suggested retail price (MSRP) in place of historical purchase cost, addition of commodity price index variables as predictors, utilization of moving averages for purchase cost, examination of other equations with a high quality of fit (high R-square value), and creation of simple linear models. These strategies were tested and achieved mixed results.

Ultimately, a combination of strategies was chosen as the best alternative for dealing with the forecasting issues, beginning with a simplification of the model generating process. It was discovered that many of the polynomial, logarithm, exponential, and power models developed by the statistical analysis software produced a reasonable fit for the data; however, the vast majority resulted in a decreasing, or otherwise counter-intuitive, projection of purchase cost. For classcode 430070, it was determined that the simple linear model provided a reasonably good fit for the data while projecting an increasing purchase cost in the future. Per these results, a linear model was subsequently developed for all of the classcodes in the database.

To determine whether an automated process could be implemented to create and evaluate linear models for forecasting purchase costs, a series of test runs were completed to develop an algorithm. These tests were carried out in EXCEL and involved the manual evaluation of 75 classcodes. Each classcode was evaluated by determining if a linear model, created from the historical TERM data, met thresholds for sample size, goodness of fit, and slope. The thresholds were established as follows: sample size greater than 6 entries (or years for which purchase cost data exists within the last 20), R-squared value greater than 0.60, and slope of the linear model greater than 0. The intent was for a linear model that passes all three checks to be chosen to forecast the purchase cost. It was determined that a linear model would be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of application in an algorithm, and a relatively good fit overall for any trends in the data. If any of the aforementioned thresholds are not met by the created model, then a default option is utilized. The purpose of this strategy is to provide a fail-safe to ensure that an increasing purchase cost is always forecasted. The default option for forecasting the purchase cost was chosen to be a formula where one-half of the inflation rate is multiplied by the current year’s purchase cost to establish the value for the subsequent year. Specifically, the purchase cost for each future year is based on the previous year’s adjusted purchase cost multiplied by one plus one-half of the inflation rate. This strategy was chosen based on input from prior meetings with TxDOT personnel where it was suggested that the inflation rate be used as a multiplier in order to guarantee an increasing purchase cost is forecasted.

Before finalizing the algorithm for implementation in the software, a check was initiated to ensure the data sets used to create the linear models were thoroughly scrutinized. In addition to the SAS macro based data cleaning process (1), another outlier removal procedure was implemented as part of the algorithm to eliminate major outliers from the data before the linear models are created by the software. With the outlier removal process and the three threshold tests determined, along with the primary and secondary (default) forecasting options established, the details for the algorithm were finalized and it was implemented using a SAS macro.

3.1.2. Down Time Cost Forecasting
A review of reports conducted for the US Army led to the identification of a number of strategies for estimating down time cost \((19, 20)\). These strategies could involve specific information about fleet operations, possible failures, and the costs or impacts associated with those failures, or they could involve a minimal amount of information including the number and length of down time related events. The reports consistently identified the use of equipment or vehicle rental rates as an estimate for down time. This would result in an estimate that is proportional to the type of equipment needing repair. While this doesn’t involve estimating labor expenses and other consequential costs, a risk factor could be implemented as a simplified approach to account for those costs which are difficult to quantify \((20)\).

In the original version of the ERO software, as well as in the TERM process previously used by TxDOT, a baseline rate of $25/hr was used as the down time rate for all classcodes. However, it was decided that this rate would not adequately assess the difference in cost associated with down time for different types of vehicles or equipment and the varying nature of their assigned tasks. To better account for the cost of down time in the optimization engine developed for TxDOT, the associated rental rate was chosen as an adequate estimate for each classcode.

The rental rate was chosen based on the established precedence for its use \((19, 20)\) and due to the limited information available relative to down time in the TxDOT database. The only information provided is the number of annual, down time hours incurred for each vehicle. To accomplish the task of assigning a down time cost, the rental rate for each classcode was determined using information obtained from various sources in the equipment and vehicle rental industry. An appropriate match and subsequent rental rate was found for many of the classcodes. However, several rates had to be estimated based on similar vehicle types or for equipment assigned tasks of similar importance. In the end, a daily rental rate was established for all (i.e., 194) classcodes in the database.

In addition, it was determined that a risk factor would be an appropriate metric to account for down time associated with vehicles and equipment that perform mission critical tasks, as well as those which are difficult to adequately substitute with a rental. Risk factors were chosen for each classcode ranging from one to three. Those with a risk factor of one represent vehicles or equipment units that are easily replaced and/or are used to perform more menial tasks. Those with a risk factor of three were deemed mission critical or not easily substituted. The base rental rates for each classcode are subsequently multiplied by the risk factor using a SAS macro to establish the final down time rate used by the program.

### 3.2. Optimization Challenges

#### 3.2.1. SDP Modeling

As mentioned, the SDP method is undoubtedly the preferred and more practically feasible approach (versus DDP) for solving the ERO problem because it explicitly considers the uncertainty in the annual vehicle utilization and the O&M cost accordingly. However, the lack of large enough and dependable data sets for some classcodes/equipment units may prevent the SDP solution from generating solutions as reliable as possible. In this regard, the SDP modeling approach produces several challenges which require additional attention and effort. For example,
there is a phenomenon commonly termed “curse of dimensionality” when developing an SDP-based ERO solution. Two SDP approaches (SDP 2-Level and SDP 3-Level) have been developed based on the categorization of annual equipment utilization each method uses (16). The SDP 2-Level approach uses simple high and low utilization levels, while the SDP 3-Level approach uses high, low, and medium utilization levels. For the SDP naïve approach, the total number of asset utilization levels at each equipment age (i.e., nodes) grows exponentially as the equipment age increases, even for a simple annual low or high mileage utilization case. As a result, particular attention has been paid to the SDP state-space growth, and special scenario reduction techniques have been developed to resolve the “curse of dimensionality” issue that is inherent to the DP method to ensure that computer memory and solution computational time required will not increase exponentially with an increase in time horizon (16, 17).

Such SDP modeling challenges have been overcome using scenario reduction strategies in the developed ERO software. The computer memory and software computational time after the scenario reduction treatments have been significantly reduced compared to the naïve DP method and both now increase only linearly with an increasing time horizon (16, 17).

3.2.2. ERO under Budget Constraints

The economic recession has resulted in limited funding, influenced by periodic budget cuts, and imposed many economic and human resource constraints for government and state agencies such as TxDOT. Consequently, an important issue has surfaced: As future funding levels become more uncertain, the lack of sufficient funds necessary for optimal vehicle replacement when suggested by the ERO software becomes very likely. If optimal replacement is unfeasible due to budget constraints, then what is the cost to the department of NOT replacing equipment when it is recommended? It is expected that repair costs for fleet equipment may increase rapidly as equipment ages and down time costs may grow significantly as the fleet is downsized or “right-sized” because duplicate equipment items may not be available to substitute when critical items are down. Therefore, the ERO problem under budget constraints (which realistically exist for government agencies and private fleet sectors) requires some special attention.

To meet this challenge and solve the ERO problem under budget constraints, the cost of NOT replacing an equipment unit when it should be replaced is first estimated by comparing the total cost of the optimal DDP/SDP solution to the minimum total cost incurred when delaying the replacement of equipment by a specified number of years. The increases in cost are quantified for each feasible replacement year (which was previously defined by the TxDOT fleet manager as TxDOT’s current benchmark replacement year plus or minus 3 and not to exceed 20 years) and are used as inputs for the second round of optimization. Next, based on these cost inputs, Knapsack programming at the second round of optimization (which can explicitly consider any annual budget constraints and possibly other constraints specified by the fleet manager) is developed and used to select the equipment units for annual replacement from a solution space that consists of all of the equipment units that are eligible for replacement. The main objective of this Knapsack programming is to maximize the benefits produced (i.e., minimize the total cost increases due to delaying the equipment replacement) in order to satisfy a combination of both TxDOT’s short-term and long-term interests. As a result, the developed ERO software is very
general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles, either with or without annual budget considerations.

3.3. Software Implementation Challenges

The DDP method generates the classcode-level cost/mileage forecast for each equipment age using all the available data. Conversely, the SDP method partitions the same data into separate vehicle utilization levels (such as - High, Medium and Low for the SDP 3-Level approach) in order to generate the cost/mileage forecasts and associated probability distributions for each utilization level at each equipment age ($16, 17$). As such, SDP can produce more realistic/reliable results when sufficient data is available. However, adequate data only exists for certain classcodes in the current TxDOT database. The other classcodes simply do not have enough data collected for the time being. In case of insufficient and/or missing data for any equipment age, proper default entries with equivalent probabilities to existing data need to be carefully generated by a SAS macro based on a meticulous analysis of the historical data to preserve the SDP-based ERO solution quality. Such SAS-generated data will be used as inputs to the SDP optimization engine to make optimal keep/replacement decisions. In addition, since the ERO software provides an option for the user to loop through all equipment units for a specific classcode (or all classcodes) for a specific district (or all districts), the ERO software must be developed with an explicit consideration of using the best computer data structures while taking into account both computation speed and memory usage. It has taken a significant amount of time and effort to overcome these challenges and to develop a well-tested and validated SDP-based ERO software program which can explicitly account for the ERO problem under the uncertainties with the annual vehicle utilization and O&M cost.

4. OPPORTUNITIES

After overcoming all of the challenges mentioned above, the ERO solution software developed by the research team as a result of the two TxDOT projects is universal and can be used to make optimal keep/replacement decisions with or without uncertainty in vehicle utilization for both brand-new and used vehicles, with or without annual budget considerations. In other words, the developed solution methodology can be used to: 1) Provide a general guide for the equipment keep/replacement decisions (i.e., how many years to keep) for a particular classcode containing brand-new equipment without considering any budget constraints; 2) Select the equipment units for annual replacement from a solution space that is composed of all the candidate equipment units that are eligible for replacement based on the annual budget and other constraints, if any ($16, 17$). It should also be noted that although all numerical results are essentially dependent upon the specific classcode chosen, after comprehensive testing it was found that numerical results of all classcodes seem to follow some similar patterns and exhibit some shared general characteristics. To this effect, the following section uses the real TxDOT TERM data ($3$) and describes some interesting and representative numerical results using two classcodes, 420010 and 520020, as an example for the light vehicle and heavy vehicle classes, respectively. The related characteristics are discussed below.

4.1. ERO Computation Time
The computational time of the ERO software for all classcodes using each solution approach was examined. It was found that the computational time is very similar and uniform for the DDP and SDP 2-Level (High and Low annual vehicle usage) approaches, and it takes an average of 10 seconds for the software to provide the optimized decision for each classcode using either method. It takes a total of about 32 minutes to loop through all (i.e., 194) classcodes and output all optimized solutions in an EXCEL file for either of the “Current Trend” or “Equal Utilization” options. However, the SDP 3-Level (High, Medium, and Low annual vehicle usage) approach appears to be less uniform and most classcodes take more time to run; the average for this approach was nearly 30 seconds for the ERO software to provide the optimized decision for each classcode with probabilistic vehicle utilization. Therefore, it takes a total of about 97 minutes to loop through all (i.e., 194) of the classcodes and output all optimized solutions into an EXCEL file for both “Current Trend” (in which the probability distribution of the vehicle utilization is forecasted based on the historical data) and “Equal Utilization” approaches (15, 16, 17).

4.2. ERO Solution Quality

A comparison of the solution quality for the DDP solution, the SDP 2-Level and 3-Level optimization solutions, and the current benchmark solutions for classcodes 420010 and 520020 is provided in Table 1. As can be seen, the objective function values (represented in $ value) for each DP approach are smaller (more desirable) than for the corresponding benchmark solutions for both classcodes. This is expected because each DP approach ensures that all solution paths (which certainly include the current purely experience-based replacement benchmark solution) are explored using a recursive procedure. This guarantees that the optimal solution is also found by selecting the decision path with the minimum total cost over the definite horizon (determined by the benchmark year).

As one can see from Table 1, using classcode 420010 with the “current trend” approach as an example, the SDP 2-Level approach results in the most savings and suggests 5 replacements over the 20 year window, while the benchmark solution recommends replacement at years 10 and 20 only. While the SDP 3-Level solution and the DDP solution offer similar replacement strategies, the difference in savings comes from the difference in the expected costs associated with each approach. These results indicate that using the developed SDP-based ERO software can significantly improve the replacement procedures and can result in substantial cost savings every year. Specifically, for classcode 420010, the estimated savings is about $5,464.40/20 = $273.22 per year for a single piece of equipment using the SDP 2-Level approach. For classcode 520020 the SDP 2-Level solution estimates a cost savings with replacement at years 6, 13, and 20 of $8,631.65/20 = $431.58 per year, which is much larger than either the DDP or SDP 3-Level solution. The average cost savings for both classcodes is estimated at ($273.22 + $431.58)/2 = $352.40 per year for the SDP 2-Level approach. Considering there are 194 classcodes used by TxDOT and, on average, each classcode includes 84 pieces of equipment, a cost savings of $352.40*194*84 = $5,742,730.77 might be expected. An also-significant cost savings of $2,599,171.26 and $2,506,389.98 for the DDP and SDP 3-Level approach can be estimated, respectively, using the same calculation method. Therefore, all three approaches have produced promising results and one might expect a significant cost savings of several million dollars annually for the agency using any of the DP approaches (16) compared to the current TxDOT benchmark decision process.
The results provided above were run without explicitly considering the annual budget constraint, which can realistically exist for government agencies and private fleet sectors. As mentioned before, the developed ERO software can also be used to select the equipment units for annual replacement based on this constraint. For example, preliminary results indicate that a significant amount of cost savings can be estimated using our developed solution methodology when considering an annual budget of 15 million dollars and TxDOT’s current TERM data (16).

Table 1. Solution Quality Comparisons between the DDP and SDP Optimized Solutions and the Current Benchmark Solutions for Classcodes 420010 and 520020

<table>
<thead>
<tr>
<th>Year</th>
<th>Classcode</th>
<th>DDP Approach</th>
<th>SDP 2-Level Approach</th>
<th>SDP 3-Level Approach</th>
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The table compares the cost savings achieved by the DDP and SDP approaches with the current benchmark solutions for Classcodes 420010 and 520020. The data includes the cost savings for each approach and comparison with the benchmark solutions for both classcodes.
5. SUMMARY AND FUTURE RESEARCH

In this paper, some of the challenges and opportunities associated with equipment replacement decision making experienced during these projects are discussed in detail. A comprehensive review of the state-of-the art and state-of-the practice literature on the ERO problem was first conducted. The developed ERO software components and functionalities were then presented. Several challenges in terms of statistical modeling (including purchase cost forecasting and downtime cost estimating), optimization (in terms of SDP modeling and ERO under budget constraints), and software implementation (particularly for the SDP approach) that were faced by the research team during the ERO software development process were described. Detailed information as to how such challenges have been overcome and turned into opportunities using current TxDOT data have also been presented. In particular, a fail-safe strategy has been developed to resolve the issue with negative forecasted purchase costs and to ensure an always increasing purchase cost forecast. This was implemented using a software algorithm that checks thresholds for sample size, goodness of fit, and slope of the linear regression model using the historical TERM data. The rental rate and risk factor were used to improve the realism and quality of downtime cost forecasts. Special scenario reduction techniques have also been developed to resolve the “curse of dimensionality” issue that is inherent to the DP method to ensure that the computer memory and solution computational time required will not increase exponentially with an increase in time horizon. A knapsack programming was incorporated to solve the ERO under budget constraints. Finally, real opportunities and the promising future for the ERO software were discussed and supported by comprehensive numerical results and their implications. Here, the software computational time and solution quality have been demonstrated to be very encouraging, and substantial cost-savings have been estimated using the ERO software.

The experience with the ERO problem using the developed software program indicates some other challenges exist that still need attention. Issues persist with forecasting future, annual O&M costs and vehicle utilization, as well as O&M cost per mile or hour for the Cost Equal Mileage method that must be addressed, and the current models need refinement. Also, the impact of the uncertainty with determining future purchase costs, downtime costs, and O&M costs on the ERO keep/replacement decision and the total cost needs further investigation. It is believed that as this line of research matures and data accumulates, the software can be of practical use to provide even more reliable and better quality results.

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REFERENCES


