Equipment Replacement Decision Making: Opportunities and Challenges

by Wei (David) Fan, Mason D. Gemar, and Randy Machemehl

The primary function of equipment managers is to replace the right equipment at the right time and at the lowest overall cost. In this paper, the opportunities and challenges associated with equipment replacement optimization (ERO) are discussed in detail. First, a comprehensive review of the state-of-the art and state-of-the practice literature for the ERO problem is conducted. Second, a dynamic programming (DP) based optimization solution methodology is presented to solve the ERO problem. The Bellman's formulation for the ERO deterministic (DDP) and stochastic dynamic programming (SDP) problems are discussed in detail. Finally, comprehensive ERO numerical results and implications are given.

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 fleet costs, which typically include the acquisition, operating and maintenance cost, and salvage value over a definite or infinite horizon.

Much research has been undertaken in equipment replacement optimization (ERO), including the Texas Department of Transportation's (TxDOT) ongoing equipment replacement optimization efforts. 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 is available elsewhere[1]. That review shows that previous research efforts made can be classified into and solved using three solution approaches.

The first is the Minimum Equivalent Annual Cost approach (EAC). In this 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). This assumption is sometimes referred to as "stationary cost" by some researchers[1] 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]

The second is the Experience/Rule-based approach, which is used in many state DOTs to make keep/replacement decisions for equipment, particularly during the early stages of ERO implementation. For example, TxDOT uses threshold values for age, equipment use, and repair cost as inputs for replacement (TxDOT Equipment Replacement Model - TERM 2004). This approach can work well for the fleet manager under certain circumstances. For example, current threshold values for dump trucks with tandem rear axles for age, use, and repair cost are 12 years, 150,000 miles, and 100%, respectively. As a result, a State Series 990d dump truck with tandem rear axles, a gross vehicle weight of more than 43,000 pounds, which is 12 years old, is considered as having accumulated 150,000 miles of use and repair costs of more than 100% of the original purchase cost (including net adjustments to capital value). Despite its simplicity, the use of this rule depends heavily upon the fleet manager's engineering judgment and experience with ERO.

The third is the Dynamic Programming (DP) approach in which 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 operating and maintenance 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. An example that uses the DP approach can be seen in Nair and Hopp (1992). Recently, Richardson et al. (2013) used a new real options approach to solving the optimized asset replacement strategy in the presence of lead time uncertainty.

There have been numerous researches on ERO with finite time horizon using the Deterministic Dynamic Programming (DDP) approach (Hartman and Murphy 2006, Hartman and Rogers 2006, Hillier and Liberman 2005, Wolsey 1998, Nemhauser and Wolsey 1999). However, almost all previous researches are devoted to the DDP solution formulation and its limited applications to extremely simplified case studies and/or small examples. To the best knowledge of the authors, there have been no research efforts made so far (except Fan et al. 2012a, 2012b, and Figliozzi et al. 2011) to apply such DP approaches to solving the real-world ERO problem. In previous research, a comprehensive DP-based optimization solution methodology has been developed to solve the ERO problem. The developed ERO software consists of three main components: 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; a DP-based optimization engine that minimizes the total cost over a defined time horizon; and 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.

When using the DDP approach, both vehicle usage and annual operating and maintenance costs are assumed to be constant or predetermined. However, due to randomness in real operations, these expected equipment utilizations are not normally realized in practice, thus invalidating the replacement optimization decisions in some aspects.

The stochastic dynamic programming (SDP) approach is undoubtedly the preferred approach to solving the ERO problem because it can explicitly consider the uncertainty in vehicle utilization and the annual operating and maintenance cost accordingly. Meyer (1971), perhaps due to computational constraints, is one among the very few to study the ERO problem under uncertainty. With advances in computing technology, a lot of research has been done to examine the ERO problem under uncertainties during the past decade, as can be seen in Hartman and Rogers (2006). However, none of these previous researches, except Fan et al. (2012b) and Figliozzi et al. (2011), uses real-world fleet cost/usage data, and all are limited and based on small examples. As a result, many underlying characteristics of the ERO SDP problem have yet to be explored and identified. To the best knowledge of the authors, this is the first ERO SDP software that is targeted at a real-world application (using TxDOT's current fleet data) and can explicitly consider uncertainty in vehicle utilization and annual operating and maintenance cost. This software is very general and can be used to make broad statements regarding the ERO problem. Nonetheless, it demonstrates the software's promising feasibility for large-scale applications. When enough cost/mileage data are collected, the SDP-based optimization solution can be of immediate use and will yield substantial cost savings for years to come in the fleet management industry worldwide.

ERO MODEL FORMULATION

General DP Characteristics

Following Bellman (1995), the basic features that characterize DP solution algorithms can be presented as follows: The problem can be divided into stages with a policy decision required at each stage. The stages are usually related to time and are often solved by going backwards in time. Each stage has a number of states associated with it. The decision at each stage transforms the current state at this stage to a state associated with the beginning of the next stage (possibly with a probability distribution applied). The solution procedure is designed to find an optimal policy for the overall problem, i.e., a prescription of the optimal policy decision at each stage for each of the possible states. Given the current state, the optimal policy decision for the remaining stages is independent of decisions made in previous stages. The solution procedure begins by finding the optimal policy for the last stage. A recursive relationship is available to traverse between the value of the decision at a stage N and the value of the optimum decisions at previous stages N+1. When using the recursive relationship, the solution procedure starts at the end and moves backward stage by stage – each time finding the optimal policy for that stage – until the optimal policy starting at the initial stage is found (Bellman 1995, Bellman 2003, Bertsekas 2001, Wagner 1975, Waddell 1983, Hartman 2005, Hartman and Murphy 2006).

DP can generally be classified into two categories: DDP and SDP. For DDP, the state at the next stage is completely determined by the state and policy decision at the current stage. In SDP, the state at the next stage is not completely determined by the state and policy decision at the current stage. Rather, there is a probability distribution applied for what the next state will be. However, the probability distribution is still determined entirely by the state and policy decision at the current stage (Bellman 2003, Wagner 1975, Meyer 1971). In SDP, the decision maker's goal is usually to minimize expected (or expected discounted) cost incurred or to maximize expected (or expected discounted) reward earned over a given time horizon.

DP Model Formulation

The TxDOT fleet manager identifies equipment items as candidates for equipment replacement one year in advance due to the fact that generally one year is required to allow sufficient time for procurement and delivery of a new unit of equipment. Since the TxDOT fleet manager makes decisions as to whether to keep or replace a piece of equipment at the beginning of each year, it is very natural to consider each year a stage. As a result, the year count (or index) is the stage variable in this paper and the age of the equipment in service at the beginning of each year is the state variable. The TxDOT fleet manager highly recommends that all equipment be salvaged at the end of a planning horizon of 20 years. In other words, it is assumed that an equipment unit will be kept no longer than 20 years. It is expected that the value of the planning horizon selected by the fleet manager may have some impacts on the equipment optimal keep/replacement decisions. However, it is also believed that 20 years is a very reasonable value and is therefore highly recommended for ERO problems of state DOTs.

The equipment purchase cost model is year-based, the annual operating and maintenance cost and the usage of the equipment unit are both age-based, and the salvage values are dependent upon both the model year and equipment age. All these data come from SAS as outputs of the SAS macro-based Data Cleaner and Analyzer and act as inputs to the DDP-based optimization engine. Moreover, it is realized that it is standard practice to allow for discounting of future costs in any DDP model and solution process. Put another way, solving the ERO problem using the dynamic programming approach requires all costs (such as annual operating and maintenance costs, including all repairs, regular maintenance and down time penalty costs, and salvage values, as well as purchase costs of the new model year). At each stage, such costs must be converted from the equipment model year (for the equipment purchase cost) and/or calendar year (for annual operating and maintenance costs and salvage value) to a benchmark year using an inflation rate. Such calculations for the discounting of future costs have been successfully performed.[1]

DP SOLUTION APPROACH

Bellman's Formulation for the ERO DDP Problem

Bellman (1995, 2003) introduced the first DDP solution to the finite horizon equipment replacement problem where the age of an asset defines the state of the system with the decision to keep or replace an asset made at the end of each period (stage). This paper implements the Bellman DDP approach so that the solution caters to TxDOT's needs in solving the ERO problem.

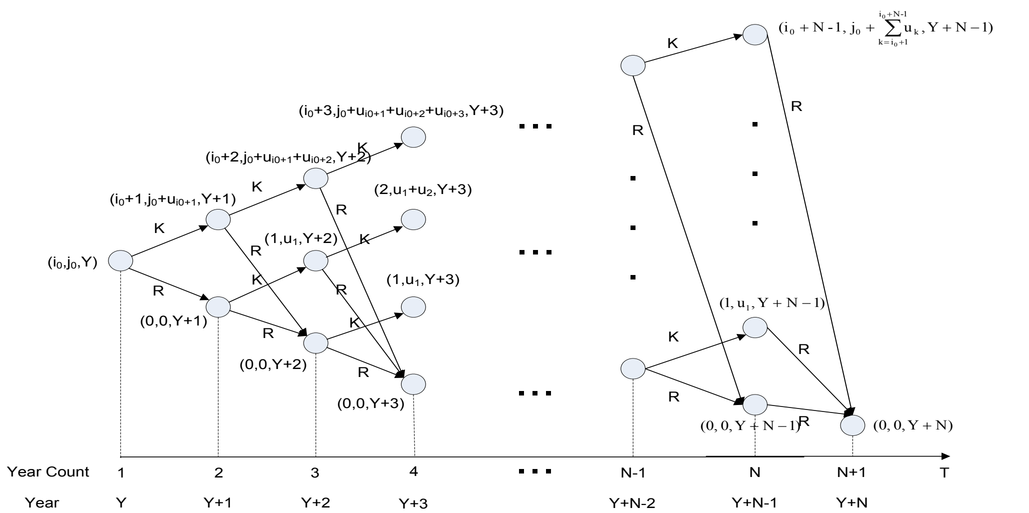
In a typical Bellman network, each node represents the age and the usage (i.e., mileage/hours) of the asset at that point in time, which is also the state space of the model. Each arc represents the decision to either keep (K) or replace (R) an asset. Keeping the asset connects nodes n (i.e., n-year-old) and n+1 (i.e., n+1-year-old) while replacing the asset is shown by an arc connecting n and zero. An optimal policy with this model, in the form (K, K, R, K, K, …), gives the optimal decision at the beginning of each year. If an asset can be retained for a maximum of periods, then the maximum number of states in a period is N. For an N-period problem, since there are a maximum of two decisions for any state, the problem can be solved using the following calculation: O (State of year 1 + State of year 2 + … + State of year N) = O (1 + 2 + 3 + … + N + 1) = O($\frac{N(N+1)}{2}$+1) where O represents computer complexity. Therefore, the computer complexity of Bellman's algorithm is O(N^2). Again, detailed information about Bellman's equation for the ERO DDP problem can be seen elsewhere.[1]

Bellman's Formulation for the ERO SDP Problem

When Bellman's approach is used in the SDP method to solve an ERO problem, a phenomenon, commonly termed "curse of dimensionality," appears. For example, the ERO SDP solution procedure, without scenario reduction treatment, has a general state-space issue that can result in exponential growth in computer memory and software computational time with increases in time horizon. Careful consideration and special treatments have been used to resolve these issues, and the computer complexity for stochastic dynamic programming is still O(N^2) using the special treatment methods developed by Fan et al. (2012b).

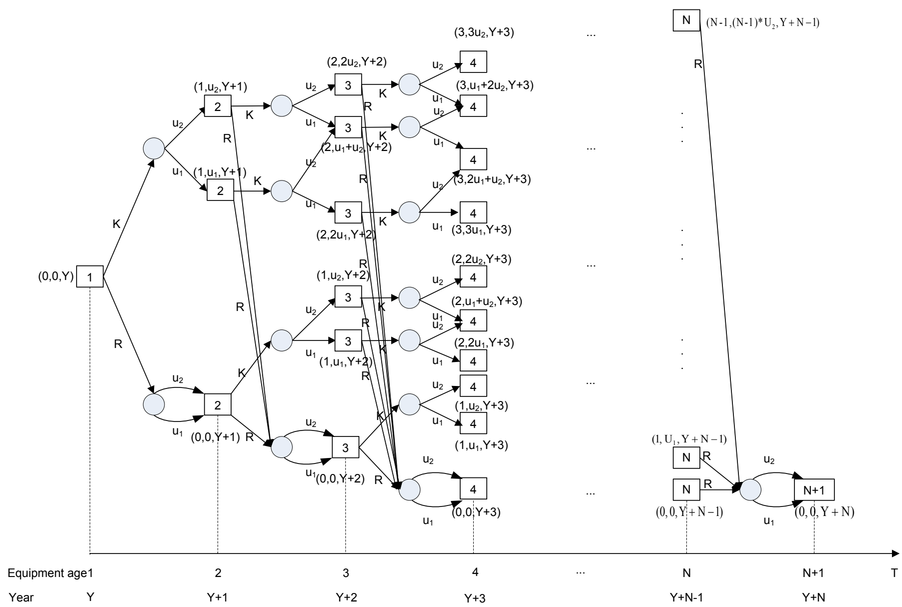
Figure 2 shows a complete "Keep-Replace" Bellman formulation example starting with a brand-new equipment unit for the ERO SDP problem, with uncertainty in vehicle utilization for the SDP-2Level case, after conducting the scenario reduction treatment. In Figure 2, the square nodes represent the decision to either keep or replace the equipment unit. The circular nodes represent chance nodes, as the equipment utilization level is uncertain and the path taken from these nodes defines the cumulative equipment utilization in the next stage. The path taken from the circular nodes are defined as and which represent two feasible (i.e., the high and low) equipment utilization levels. Additionally, all nodes at time N are connected to a dummy node at time N+1, which represents the salvage value of the equipment unit after the final stage of the finite horizon problem. It should also be noted that the total cost would include the purchase cost, the expected annual operating and maintenance cost, and salvage value, as previously mentioned.

Figure 1: Bellman's Formulation



K – Keep asset
R – Replace asset
Note:
a. $(i_0 + N - 1, j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k, Y + N - 1)$ represents the status of a vehicle which is $(i_0 + N - 1)$-year old with its accumulative mileage being $(j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k)$ at the beginning of year $(Y + N - 1)$. u_k denotes the usage during the year at the end of which the equipment becomes k-year old. Similar notation follows.
b. The salvage value is associated with "R" decision. The decision is made at the beginning of each year where the starting node is located. The salvage value is referred to as the value of equipment age at the end of that year. The operating/maintenance cost associated with "K" decision is related to the equipment age at the end of that year.

Figure 2: SDP Formulation for ERPO Under Asset Utilization Uncertainty: Two-Level Case with Scenario Reduction Treatment



K – Keep asset
R – Replace asset

Note:
a. (i, U_i, Y) represents the status of a vehicle which is i-year old with its accumulative mileage used being U_i during the i years at the beginning of year Y. Similar notation follows.
b. The salvage value is associated with "R" decision. The decision is made at the beginning of each year where the starting node is located. The salvage value is referred to as the value of equipment age at the end of that year. The operating/maintenance cost associated with "K" decision is related to the equipment age at the end of that year.

SOFTWARE DEVELOPMENT AND FUNCTIONALITIES

SDP Computer Implementation Techniques

To successfully implement the Bellman formulation to solve the ERO SDP problem, an efficient and effective data structure is designed and then implemented by developing Java computer programs. The model year-based equipment purchase cost, the equipment age- and model year-based salvage value, and the equipment age- and mileage-based annual operating and maintenance cost data, along with corresponding probability distribution for each year that come from SAS are read and processed by the Java codes through three steps/layers within the optimization engine. The first layer is reading the equipment class code, the second layer is reading the equipment age, and the third layer is reading the equipment utilization and associated probability (to accommodate the different equipment utilization levels). A series of dynamically allocated arrays are developed to store the data[1]. The Bellman approach, as presented earlier, is then solved backward and the recursive functions are called efficiently.

SDP Software Development and Functionalities

The developed DDP software considers two approaches for the ERO problem: First, it assumes that the "current trend" continues. That is, it uses all the information from the current TERM data that are "error- and outlier-free" and assumes that the same trend will continue for future years. For example, the current TERM data show that equipment utilization decreases as equipment gets older and therefore it is assumed that this trend will continue[1]. Second, it assumes "equal utilization." That is, it takes the average mileage across all equipment with the same class code and uses this number for the utilization of all equipment during that year. Even with this, it is noteworthy that year-to-year utilization for the same class code can be different. In subsequent sections, numerical results are presented to show an example of the differences in the equipment keep/replace decisions between these two approaches.

Many other functions have been incorporated into the DP-based ERO software, including the following: The software allows the user to specify budget constraints, as well as the time window that the programming will use during optimization. The software allows users to selectively "clean the data" by removing missing data related to any cost and mileage variables and outliers associated with any non-missing data. And the users can run the software using SAS automatically generated cost data or use editable cost data that they provide manually at the beginning of each year. The user can choose from several different approaches, namely: current "cost trend" or cost "equal utilization" (as explained earlier in this section), DDP or SDP, and the Bellman (1995, 2003) or Wagner (1975), all mentioned and defined before. The user can also choose to delay the equipment replacement or replace it early by specifying a positive or negative delay time. The software can also run an optimization on any individual used piece of equipment from a specific class code, on all equipment units from one specific class code or from class codes, or on brand new equipment units from either one specific class code or all class codes. The software gives an EXCEL report for the cost savings by comparing the optimal solution with the benchmark rules, 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. Finally, users can add new annual TERM data at the beginning of each year and make dynamic keep/replace decisions for any chosen class code or equipment unit.

OPPORTUNITIES AND CHALLENGES

The developed ERO solution software in this paper is very general and can be used to make optimal keep/replace decisions with or without uncertainty in vehicle utilization for both brand-new and used vehicles, both with or without annual budget considerations. In other words, the methodology can be used to: provide a general guide for the equipment keep/replacement decisions (i.e., how many years to keep) for a particular class code containing brand-new equipment without considering any budget constraints; and select 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. Also, it should be noted that all numerical results are essentially dependent upon the specific class code chosen. However, after comprehensive testing, it was found that numerical results of all class codes seem to follow similar patterns and exhibit some shared general characteristics. In this regard, the following section uses the real TxDOT TERM data (TERM 2004) and describes some interesting and representative numerical results using two class codes, 420010 and 520020, as an example for light vehicle and heavy vehicle classes, respectively. Related characteristics are discussed as follows.

Opportunities

The computational time of the ERO software for all class codes and each solution approach was examined. It was found that the computational time is very uniform for the DDP and SDP 2-Level approaches and it takes an average of 10 seconds for the software to provide the best optimized decision for each class code. It takes a total of about 32 minutes to loop through all (i.e., 194) class codes and output all optimized solutions in an EXCEL file for the "current trend" or "equal utilization" approach. However, the SDP 3-Level approach appears to be less uniform and most class codes take more time to run; the average for this approach was nearly 30 seconds for the ERO software to provide the best optimized decision for each class code with probabilistic vehicle utilization. Therefore, it takes a total of about 97 minutes to loop through all (i.e., 194) class codes and output all optimized solutions in an EXCEL file for the "current trend" approach in which the probability distribution of the vehicle utilization is forecasted based on the historical data.

A comparison of the quality of the DDP solution, the SDP 2-Level and 3-Level optimization solutions, and the current benchmark solutions for class codes 420010 and 520020 is given in Table 1. As can be seen, the objective function values (represented in dollar value) for each DP approach are smaller (more desirable) than for the corresponding benchmark solutions for both class codes. 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 by solving backward. This guarantees that the best solution is also found by selecting the solution path with minimum total cost over the definite horizon (determined by the benchmark year).

In addition, the total cost of the benchmark solutions for the DDP, SDP 2-Level, and SDP 3-Level approaches are all different. This is expected because the DDP approach uses the class code-level cost/mileage forecast for all future years to calculate the benchmark decision year. On the other hand, both SDP approaches generate and use cost/mileage forecasts for each individual class code and all the vehicle utilization levels (low-high for 2-Level, or low-medium-high for 3-Level) and their associated probability distributions for all future years to determine the benchmark decision year. This can cause the expected cost/mileage data to be slightly different between the different solution approaches.

As one can see from Table 1, using class code 420010 with the "current trend" approach as an example, the SDP 2-Level approach results in the most savings and suggests five replacements over the 20-year window, while the benchmark solution suggests replacement at years 10 and 20 only. While the SDP 3-Level solution and the DDP solution offer similar replacement strategies, the

Table 1: Solution Comparisons Between DDP, SDP, and Current Benchmark Solutions for Class Codes 420010 and 520020

		Year	DDP Approach				SDP 2-Level Approach				SDP 3-Level Approach			
			DDP Solution		Benchmark Solution		SDP Solution		Benchmark Solution		SDP Solution		Benchmark Solution	
			Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost
Classcode	420010	1	K	$2,881.39	K	$2,881.39	R	$5,269.29	K	$2,469.76	K	$2,469.76	K	$2,469.76
		2	R	$9,050.29	K	$3,320.66	R	$6,101.20	K	$3,448.38	R	$8,794.86	K	$3,065.23
		3	K	$2,881.39	K	$3,782.13	K	$2,469.76	K	$3,696.17	K	$2,469.76	K	$3,724.82
		4	K	$3,320.66	K	$4,256.11	K	$3,448.38	K	$4,038.96	K	$3,065.23	K	$4,198.20
		5	K	$3,782.13	K	$4,732.92	K	$3,696.17	K	$4,503.90	K	$3,724.82	K	$4,783.81
		6	K	$4,256.11	K	$5,202.88	K	$4,038.96	K	$5,070.60	R	$15,601.30	K	$4,967.72
		7	R	$17,989.34	K	$5,656.32	R	$17,760.33	K	$5,556.50	K	$2,469.76	K	$5,478.87
		8	K	$2,881.39	K	$6,083.55	K	$2,469.76	K	$6,007.50	K	$3,065.23	K	$5,779.37
		9	K	$3,320.66	K	$6,474.89	K	$3,448.38	K	$6,474.89	K	$3,724.82	K	$6,151.15
		10	K	$3,782.13	R	$25,673.63	K	$3,696.17	R	$25,478.75	K	$4,198.20	R	$25,413.79
		11	K	$4,256.11	K	$2,881.39	K	$4,038.96	K	$2,469.76	K	$4,783.81	K	$2,469.76
		12	K	$4,732.92	K	$3,320.66	K	$4,503.90	K	$3,448.38	R	$21,279.03	K	$3,065.23
		13	R	$21,887.57	K	$3,782.13	R	$21,755.29	K	$3,696.17	K	$2,469.76	K	$3,724.82
		14	K	$2,881.39	K	$4,256.11	K	$2,469.76	K	$4,038.96	K	$3,065.23	K	$4,198.20
		15	K	$3,320.66	K	$4,732.92	K	$3,448.38	K	$4,503.90	K	$3,724.82	K	$4,783.81
		16	K	$3,782.13	K	$5,202.88	K	$3,696.17	K	$5,070.60	K	$4,198.20	K	$4,967.72
		17	K	$4,256.11	K	$5,656.32	K	$4,038.96	K	$5,556.50	K	$4,783.81	K	$5,478.87
		18	K	$4,732.92	K	$6,083.55	K	$4,503.90	K	$6,007.50	K	$4,967.72	K	$5,779.37
		19	K	$5,202.88	K	$6,474.89	K	$5,070.60	K	$6,474.89	K	$5,478.87	K	$6,151.15
		20	R	$26,202.97	R	$29,674.69	R	$26,103.16	R	$29,479.81	R	$27,230.39	R	$29,414.86
			Total	$135,401.15	Total	$140,130.02	Total	$132,027.48	Total	$137,491.88	Total	$131,565.38	Total	$136,066.51
			Cost Savings	$4,728.87			Cost Savings	$5,464.40			Cost Savings	$4,501.13		
	520020	1	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53	K	$1,865.53
		2	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71	K	$2,915.71
		3	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86	K	$3,916.86
		4	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60	K	$4,864.60
		5	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55	K	$5,754.55
		6	K	$6,582.32	K	$6,582.32	R	$39,399.23	K	$6,582.33	K	$6,582.32	K	$6,582.32
		7	K	$7,343.55	K	$7,343.55	K	$1,865.53	K	$7,343.55	K	$8,567.48	K	$8,567.48
		8	K	$8,033.85	K	$8,033.85	K	$2,915.71	K	$10,042.31	K	$8,033.85	K	$8,033.85
		9	R	$47,607.00	K	$8,648.84	K	$3,916.86	K	$10,090.31	R	$47,607.00	K	$8,648.83
		10	K	$1,865.53	K	$9,184.14	K	$4,864.60	K	$11,152.17	K	$1,865.53	K	$8,309.46
		11	K	$2,915.71	R	$52,129.15	K	$5,754.55	R	$53,735.05	K	$2,915.71	R	$49,987.96
		12	K	$3,916.86	K	$1,865.53	K	$6,582.33	K	$1,865.53	K	$3,916.86	K	$1,865.53
		13	K	$4,864.60	K	$2,915.71	R	$47,495.25	K	$2,915.71	K	$4,864.60	K	$2,915.71
		14	K	$5,754.55	K	$3,916.86	K	$1,865.53	K	$3,916.86	K	$5,754.55	K	$3,916.86
		15	K	$6,582.32	K	$4,864.60	K	$2,915.71	K	$4,864.60	K	$6,582.32	K	$4,864.60
		16	K	$7,343.55	K	$5,754.55	K	$3,916.86	K	$5,754.55	K	$8,567.48	K	$5,754.55
		17	K	$8,033.85	K	$6,582.32	K	$4,864.60	K	$6,582.33	K	$8,033.85	K	$6,582.32
		18	K	$8,648.84	K	$7,343.55	K	$5,754.55	K	$7,343.55	K	$8,648.83	K	$8,567.48
		19	K	$9,184.14	K	$8,033.85	K	$6,582.33	K	$10,042.31	K	$8,309.46	K	$8,033.85
		20	R	$60,198.47	R	$57,327.35	R	$53,674.70	R	$58,768.83	R	$58,057.28	R	$57,327.35
			Total	$208,192.39	Total	$209,843.42	Total	$211,685.59	Total	$220,317.24	Total	$207,624.37	Total	$209,275.40
			Cost Savings	$1,651.03			Cost Savings	$8,631.65			Cost Savings	$1,651.03		

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 class code 420010, the estimated savings is about $5,464.40/20 = $273.22 per year for a single piece of equipment. For class code 520020, the SDP 2-Level solution estimates the cost savings with replacement for year six, 13, and 20 as $8,631.65/20 = $431.58 per year, which is much greater than either the DDP or SDP 3-Level solutions. The average of the cost savings for both class codes is estimated at ($273.22 + $431.58)/2 = $352.40 per year. Considering that there are 194 class codes used by TxDOT and on average each class code includes 84 pieces of equipment, a cost savings of $352.40*194*84 = $5,742,710.4 might be expected. As can be seen from Table 1, a significant cost savings also of $2,506,389.98 for the SDP 3-Level approach can be estimated using the same method of calculation. Therefore, one might expect a cost saving of several million dollars annually for the agency using the SDP approaches.

The results provided here were obtained without explicitly considering the annual budget constraints of government agencies and private fleet providers. However, the methodology developed in this paper can be used to select equipment units for annual replacement based on annual budget and other possible constraints specified by the fleet manager. To solve the ERO problem under such constraints, the following steps are required.

First, the cost of not replacing an equipment unit when it should be replaced is estimated by comparing the total cost of the optimal solution to the minimum total cost incurred when delaying the replacement of equipment by a certain number of years. The increases in cost are quantified for each feasible replacement year and are used as inputs to the second round of optimization. Next, the second round of optimization is used to select the equipment units for annual replacement from all equipment units that are eligible for replacement. The main objective of this step is to maximize the benefits produced and include a mixture of both TxDOT's short-term and long-term interests. Preliminary results indicate that when an annual budget of $15 million is assumed to be allocated and used, a significant amount of cost savings can be estimated by applying the solution methodology developed in this paper to optimize TxDOT's equipment replacement in the current fleet existing in the TxDOT Equipment Replacement Model (TERM) data.

Challenges

After conducting comprehensive testing, all three approaches have produced promising results and can yield significant cost savings compared with the current TxDOT benchmark decision process. Because the probabilistic nature of vehicle utilization is explicitly considered, the formulated SDP approach appears to be more practically feasible than the DDP approach. However, the lack of large enough and dependable data sets for some class code/equipment units may prevent the SDP software from generating as reliable a solution as possible. In this regard, the SDP approach is still in somewhat of an early development stage and will be more promising for a future application as this line of research matures and the data collection effort progresses. The impact of uncertain future purchase cost, down time cost, and operating and maintenance cost on the ERO keep/replace decision and its total cost also need further investigation.

SUMMARY AND FUTURE RESEARCH

In this paper, a comprehensive review of the state-of-the art and state-of-the practice literature for the equipment replacement optimization (ERO) problem is first conducted. A dynamic programming (DP) based optimization solution methodology is then presented to solve the ERO problem. Bellman's formulation for the ERO deterministic (DDP) and stochastic dynamic programming (SDP) problems are discussed in detail. Finally, comprehensive ERO numerical results and implications are given along with the opportunities and challenges associated with the equipment replacement optimization problem. The software's computational time and solution quality have been demonstrated to be very promising and encouraging, and substantial cost-savings are estimated using this ERO software. The computational experience with the ERO problem also indicates that some challenges with data collection efforts need to be met in the future. Other issues with forecasting future purchase cost, the down time cost, and operating and maintenance cost must also be addressed. As this line of research matures and data accumulate, the software can be of immediate use to provide even more reliable and better results.

Endnotes

1. This paper draws from the following previous researches of the authors: Fan, et al. (2011; 2012a, b) to provide a detailed discussion and analysis of equipment replacement optimization.

Acknowledgements

The authors want to sincerely thank Texas Department of Transportation (TxDOT) for sponsoring the research projects 0-6412 "Equipment Replacement Optimization" and 0-6693 "Equipment Replacement/Retention Decision Making." The authors also acknowledge the seasoned contributions of Duncan Stewart, Johnie Muller, Don Lewis, Karen Dennis, and Ron Hagquist of TxDOT and their staff for the input and feedback during the development of this research.

References

Bellman, R.E. "Equipment Replacement Policy." *Journal of the Society for the Industrial Applications of Mathematics* 3, (1995): 133-136.

Bellman, R.E. *Dynamic Programming*. Dover Publications, Mineola, New York, 2003.

Bertsekas, D.P. *Dynamic Programming and Optimal Control*, *Second Edition*, Athena Scientific, Belmont, MA, 2001.

Fan, W., R. Machemehl, and K. Kortum. "Equipment Replacement Optimization: Solution Methodology, Statistical Data Analysis, and Cost Forecasting." *Transportation Research Record: Journal of the Transporation Research Board* 2220, (2011): 88-98.

Fan, W., R. Machemehl, and M. Gemar. "Optimization of Equipment Replacement: Dynamic Programming-Based Optimization." *Transportation Research Record: Journal of the Transporation Research Board* 2292, (2012a): 160-170.

Fan, W., R. Machemehl, M. Gemar, and L. Brown. "A Stochastic Dynamic Programming Approach for the Equipment Replacement Optimization with Probabilistic Vehicle Utilization." *Proceedings of the 91st Annual Meeting of the Transportation Research Board*, 2012b.

Figliozzi, M.A., J.A. Boudart, and W. Feng. "Economic and Environmental Optimization of Vehicle Fleets: A Case Study of the Impacts of Policy, Market, Utilization, and Technological Factors." *Proceedings of the 90th Annual Meeting of the Transportation Research Board* (2011).

Hartman, J.C. "A Note on 'A Strategy for Optimal Equipment Replacement'." *Production Planning & Control* 16 (7), (2005): 733-739.

Hartman, J.C. and J.L. Rogers. "Dynamic Programming Approaches for Equipment Replacement Problems with Continuous and Discontinuous Technological Change." *IMA Journal of Management Mathematics* 17 (2), (2006): 143-158.

Hartman, J.C. and A. Murphy. "Finite-Horizon Equipment Replacement Analysis." *IIE Transactions* 38 (5), (2006): 409-419.

Hillier, F. and G. Lieberman. *Introduction to Operations Research and Revised CD-ROM 8 (Hardcover).* McGraw-Hill, 8th Edition, New York City, 2005.

Meyer, R.A. "Equipment Replacement Under Uncertainty." *Management Science* 17 (11), (1971): 750-758.

Nair. S.K. and W.J. Hopp. "A Model for Equipment Replacement Due to Technological Obsolescence." *European Journal of Operations Research* 63, (1992): 207-221.

Nemhauser, G.L. and L.A. Wolsey. *Integer and Combinatorial Optimization*. Wiley, Hoboken, NJ, 1999.

Richardson, S., A. Kefford, and M.J. Hodkiewicz. "Optimised Asset Replacement Strategy in the Presence of Lead Time Uncertainty." *International Journal of Production Economics* 141 (2), (2013): 659-667.

TxDOT Equipment Replacement Model – TERM. 2004. ftp://ftp.dot.state.tx.us/pub/txdot-info/gsd/pdf/txdoterm.pdf (Accessed on January 20, 2009).

Waddell, R. "A Model for Equipment Replacement Decisions and Policies." *Interfaces* 13 (4), (1983): 1-7.

Wagner, H.M. *Principles of Operations Research.* Prentice-Hall, Englewood Cliffs, NJ, 1975.

Wolsey, L.A. *Integer Programming.* Wiley, Hoboken, NJ. Wiley.

Wei (David) Fan *is currently an associate professor of civil engineering at the University of North Carolina at Charlotte. He worked as an associate professor at The University of Texas at Tyler and was a senior optimization developer in the R&D department in SAS Institute Inc. after he obtained a Ph.D. degree in civil engineering from the University of Texas at Austin in 2004. His primary research interests include operations research, transportation network modeling and optimization, traffic simulation, traffic engineering and operations, transportation planning, and pavement management systems. He has 18 years of experience with statistical and optimization computer software development and has authored more than 40 journal and conference publications and has given numerous conference and invited presentations of his research results.*

__Mason Gemar__ is a Ph.D. candidate at the department of civil and environmental engineering at the University of Texas at Austin. He specializes in traffic engineering & operations, traffic simulation, transportation planning, and operations research. He has published in numerous journals and conferences and given many conference and invited presentations of his research results.

__Randy Machemehl__ currently serves as a professor of civil engineering at the University of Texas at Austin. He is an internationally recognized scholar in the transportation system engineering field and a well-known expert in several research fields, including traffic control systems, simulation and optimization of transportation systems, psycho-physical measuring of driver behavior, and freeway bottleneck resolution. He has directed many large research projects and published more than 160 technical reports and papers.