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16. Abstract

TxDOT has a fleet value of approximately $500,000,000 with an annual turnover of about $50,000,000. Substantial cost savings with fleet management has been documented in the management science literature. For example, a 1983 Interfaces article discussed how Phillips Petroleum saved $90,000 annually by implementing an improved system for a fleet of 5300 vehicles. Scaling up to the TxDOT fleet, the corresponding savings would be around $350,000 in 2008 dollars. Similar savings were reported in a 2008 presentation by Mercury Associates.

TxDOT Research Project 7-4941 (1997), Equipment Replacement Criteria Based on LCCBA, created a SAS decision analysis tool to be used by the department in its equipment replacement process. While the 7-4941 analysis tool met project scope within the data limitations existing at the time of its delivery, an improved vehicle cost data base will now allow a more normative decision support tool for fleet replacement optimization. In this sense, optimization means minimizing the life-cycle sum of maintenance cost and replacement cost (new equipment price minus resale value). The Department needs a system which recommends whether to retain or replace a unit of equipment, given that class of equipment's age, mileage, resale value, and the cost of replacement equipment. TxDOT categorizes, accounts for, and replaces equipment based on classes of equipment; the new automated fleet optimization system must use these class codes.

The objective of this project is to (1) determine the best optimization methodology; (2) evaluate commercial fleet management systems; (3) develop the model if this is cost-effective relative to purchasing a commercial model; and (4) validate the new model as needed using data available on TxDOT's current fleet. To accomplish this project, the research team will formulate the equipment replacement optimization problem as a Mixed-Integer Linear Programming (MILP) model, and propose both Deterministic Dynamic Programming (DDP) and Stochastic Dynamic Programming (SDP) approaches to solving the Equipment Replacement Optimization (ERO) problem. Certainly, this system will be user-friendly and designed so that it can be easily used by non-technical district personnel (to evaluate individual district units against a class) and by technical division personnel (Fleet Manager) to develop optimal aggregate classcode replacement cycles.

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Equipment Replacement Optimization

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Products

This report also contains product 0-6412-P1 (Practical Guidelines on Equipment Replacement Optimization) as Appendix A. Also provided to TxDOT, along with the product, as results of this project, are the developed software code files on a USB.

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Chapter 1. Introduction

1.1 Problem Statement

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 in retaining their value may exist in the marketplace and be available for replacement. For this reason public and private agencies that maintain fleets of vehicles and/or specialized equipment must periodically decide when to replace vehicles composing their fleet. These equipment replacement decisions are usually based upon a desire to minimize fleet costs and are often motivated by the conditions of deterioration and technological changes, either separately or together (Hartman, 2005; Hartman, 2008).

According to the Texas Department of Transportation (TxDOT), 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 (TERM, 2004). Any methodology that can improve TxDOT's replacement procedures can potentially save millions of dollars.

Substantial cost savings with fleet management has been documented in management science literature. For example, a 1983 Interfaces article discussed how Phillips Petroleum saved $90,000 annually by implementing an improved system for a fleet of 5300 vehicles (Waddell, 1983). Scaling up to the TxDOT fleet, the corresponding savings would be around $350,000 in 2008 dollars. Similar savings were reported in presentations made by Mercury Associates (Mercury Associates Inc., 2002; 2005; 2007).

The equipment replacement optimization (ERO) effort is also extremely important in the context of overall fleet management efforts. For example, the best equipment replacement decision tool in the world may not be very useful if there is no funding available to purchase new vehicles to replace the old ones. An ERO decision tool can be effectively used as part of a long-range fleet replacement plan that can estimate the future budget required to meet predicted replacement needs for all future years. The primary function of equipment managers is to replace the right equipment at the right time and at the lowest overall cost. To accomplish this task, a theoretically sound and practically feasible ERO methodology must be developed to accommodate specific TxDOT needs. It is expected that a significant amount of money can thus be saved (Fan et al., 2011a).

TxDOT Research Project 7-4941 (Weissmann and Weissmann, 2002; 2003a; Weissmann, et al., 2003b), Equipment Replacement Criteria Based on LCCBA, created a SAS decision analysis tool to be used by the department in its equipment replacement process. While the 7-4941 analysis tool met project scope within the data limitations existing at the time of its delivery, an improved vehicle cost data base will now allow a more normative decision support tool for fleet replacement optimization. In this sense, optimization means minimizing the life-cycle sum of maintenance cost and replacement cost (new equipment price minus resale value). The Department needs a system which recommends whether to retain or replace a unit of equipment, given that class of equipment's age, mileage, resale value, and the cost of new equipment. TxDOT categorizes, accounts for, and replaces equipment based on classes of equipment; the new automated fleet optimization system must use these class codes.

1.2 Objectives

The objective of this report is to (1) evaluate commercial fleet management systems; (2) determine the best optimization methodology; (3) develop the model if this is cost-effective relative to purchasing a commercial model; and (4) validate the new model as needed using data available on TxDOT's current fleet. To accomplish this project, the research team will formulate the ERO problem as an Integer Linear Programming (ILP) model, and develop both Deterministic Dynamic Programming (DDP) and Stochastic Dynamic Programming (SDP) approaches to solving the ERO problem. Certainly, this system is user-friendly and designed so that it can be easily used by non-technical district personnel (to evaluate individual district units against a class) and by technical division personnel (Fleet Manager) to develop optimal aggregate classcode replacement cycles.

1.3 Expected Contributions

To accomplish these objectives, several tasks have been undertaken. A comprehensive dynamic programming (DP)-based optimization solution methodology and optimization software has been developed to solve the ERO problem. In particular, it should be mentioned that the developed ERO solution methodology is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles both with and without annual budget considerations.

An extensive review of the existing literature reveals that this is the first ERO software that is targeted at the real world application (using TxDOT's current fleet data) and caters to TxDOT's own needs. Furthermore, it is believed that this pilot work is very general and can potentially be an example to demonstrate the promising feasibility and also immediate usability of the DP-based optimization solution, which can yield substantial cost savings for years to come in the fleet management industry worldwide (Fan et al., 2011a; 2011b; 2011c).

1.4 Report Overview

The remainder of this report is organized as follows: Chapter 2 presents a comprehensive review of the state-of-the-art and state-of-the-practice literature on the ERO problem. Chapter 3 provides a detailed model formulation for the ERO problem using an integer linear programming model, and two DP solution approaches are also developed, DDP and SDP. Chapter 4 describes the solution methodology for the ERO problem, which consists of three main components: 1) A SAS Macro based Data Cleaner and Analyzer; 2) A DP-based optimization engine; and 3) A Java based Graphical User Interface (GUI). Chapter 5 presents the Java GUI and its components along with a list of different software functionalities. Chapter 6 discusses the SAS Macro Data Cleaner and Analyzer, which undertakes the tasks of raw data reading, cleaning and analyzing, as well as cost estimation & forecasting. Chapter 7 presents the DP-based optimization engine, the DDP and SDP solution approaches for the ERO problem, and the development of Bellman's and Wagner's formulations, as well as the knapsack programming and computer implementation techniques. Chapter 8 presents case studies and comprehensive statistical analyses and detailed optimization numerical results based on the real world TxDOT equipment replacement model (TERM) data using two typical classcodes as examples. Finally Chapter 9 concludes this report with a summary and a discussion of the directions for future research.

Chapter 2. Literature Review

2.1 Introduction

This chapter provides a review and synthesis of the state-of-the-art and state-of-the-practice literature on the ERO problem and commercial fleet management systems currently available worldwide. This should give a clear picture of the current situation in fleet management worldwide and the direction ERO may take in the near future.

The following sections are organized as follows. Section 2.2 describes the current ERO status within the state of Texas. Section 2.3 provides a comprehensive review of the existing ERO status and commercial fleet management systems in other state Departments of Transportation (DOTs) and private companies. Section 2.4 details past and present ERO research from four different solution approaches. Finally, section 2.5 concludes this chapter with a summary.

2.2 Existing ERO Status within the State of Texas

2.2.1 Primitive TERM

TxDOT uses the Texas Equipment Replacement Model (TERM) (TERM, 2004) to identify equipment items as candidates for equipment replacement one year in advance of need (This one year allows sufficient time for the procurement and delivery of a new unit). TxDOT's Equipment Operations System (EOS), in operation since 1984, captures extensive information on all aspects of equipment operation. This system is used to provide historical data in a computerized approach. EOS historical cost data is processed against three preset standards/benchmarks for each identified equipment class. The criteria used for replacement in the approach are 1) Equipment age, 2) Life usage expressed in miles (or hours), and 3) Life repair costs (adjusted for inflation) relative to original purchase cost (including net adjustment to capital value) (TERM, 2004).

In other words, TERM uses threshold values of age, use of an equipment unit, and repair cost as inputs for replacement. For example, current threshold values for dump trucks with tandem rear axles (referred to as classcode 540020 within TxDOT) for age, use, and repair cost are 12 years, 150,000 miles, and 100%, respectively. As a result, a dump truck with tandem rear axles, 43000+ lb. GVWR, State Series 990d, that is 12 years old, has accumulated 150,000 miles of usage, and whose life repair costs have exceeded one hundred percent of the original purchase cost, including net adjustments to capital value, meets all three criteria (TERM, 2004).

2.2.2 UTSA-TERM

Starting in 1997, UTSA created a SAS decision analysis tool to be used by the TxDOT in its equipment replacement process (Weissmann and Weissmann, 2002; Weissmann and Weissmann, 2003a; Weissmann et al, 2003b). The equipment replacement approach developed includes multi-attribute priority ranking combined with a life-cycle cost trend analysis. It allows the manager to select the attributes used to compare the challenged unit with all other active units within a desired class or group, and use the life-cycle costs and multi-attribute ranking methodologies for equipment replacement (Weissmann et al, 2003c).

While the UTSA-TERM analysis tool met project scope within the data limitations existing at the time of its delivery, an improved vehicle cost data base has been developed and will now allow a more normative decision support tool for fleet replacement optimization. It is known that there are several major improvements can be made to the UTSA-TERM model: First, although it can generate a priority list of equipment units for replacement for each classcode by comparing each other within the same classcode based on a specific method such as life-cycle cost trends, this may result in its “optimal” replacement decision being suboptimal. This is because the unit-level could have too many outliers in costs, mileage, etc. associated with each unit, and it does not track and use the classcode-level operating and maintenance cost, purchase cost, salvage value, etc. for replacement decision-making. Second, it is still very labor intensive (users have to try and get the priority replacement list for each classcode at a time - TxDOT has over 100 classcodes), heavily depends on the fleet managers’ experience (Fleet managers may have to determine and possibly try many weight sets and run the software for each, and compare many solutions before possibly reaching and selecting a final “good-looking” solution that they may be eventually satisfied with), and is not fully automated (one classcode at a time). Since TxDOT categorizes, accounts for, and replaces equipment based on classes of equipment, TxDOT needs a new, more robust fleet optimization system that must use these classcodes rather than individual pieces of equipment, can fully automate the process, and optimize the equipment keep/replacement decision based on that class of equipment’s age, mileage, resale value, and the cost of replacement equipment.

The research efforts in this report will focus on addressing these issues. The ERO solution software developed as a result of this project is an advanced and fully automated software system that incorporates robust mathematical optimization models and reliable statistical cost estimation and forecasting models. With a click of the mouse button, the “one-stop shopping” seamless software system can automatically recommend robust optimization solutions based on the built-in cost statistical analysis. To accomplish this task, Java is carefully chosen as the programming language. DP and Knapsack programming are the designed optimization solution approaches.

2.3 Existing ERO Status and Commercial Fleet Management Systems in Other State DOTs/Private Companies

2.3.1 Existing Software Programs

A significant number of software programs currently exist to assist in fleet management. One of the major fleet management software manufacturers is AssetWorks. Their programs and services are offered to a number of state DOTs and other public organizations. DOT users of AssetWorks’ software include Arizona, Minnesota, California (Caltrans), Delaware, Georgia, Maine, Michigan, Nevada, New Hampshire, New Jersey, New York, Virginia, and Washington (State Government, 2009).

2.3.2 Fleet Management Consultants

Many firms provide consultant services to fleet managers. For some firms, Mercury Associates in particular, consulting services are their primary operations. For other firms, consulting on fleet management is merely a part of an overall fleet management business model. These types of firms also work with a variety of clients on fuel management, vehicle leasing, driver management, and other services. The following sections describe several specific fleet management firms.

2.2.2.1. Mercury Associates

Mercury Associates, a Washington D.C. fleet management firm, has experience with fleets of vastly different sizes, ranging from 25 to more than 650,000 vehicles. Their clients include private companies such as Laidlaw and General Motors, the US federal government, and a wide variety of state and local governmental agencies; clients have also owned a diverse set of fleets, from fire trucks, buses, trucks, bulldozers, and many more. Mercury has worked with 28 of the 50 U.S. states (more than any other fleet management consulting firm), 33 of the 50 largest US cities, and 30 colleges and universities. Mercury also provides an outsourcing feasibility study to any agency considering contracting with the company to handle some or all of the fleet management services.

Mercury has worked with many state DOTs. Specific instances include the Delaware Department of Transportation contracting with Mercury in 2004 to perform a comprehensive fit-gap analysis of its existing information. The Delaware DOT then used this information to enhance its system of support for fleet operations (Mercury, 2009). New Mexico's DOT, which manages about 6,000 vehicles, has also contracted with Mercury for both consulting services and training in fleet management best practices (Mercury, 2009).

2.2.2.2. Automotive Resources International

ARI is the largest privately-held fleet leasing and management company in the world. Founded 60 years ago, the company today manages more than 2,000 customer fleets in North America, or over 650,000 vehicles. Many of these fleets are owned by city, county, state, and federal clients. ARI is also partnered with companies in Japan, Columbia, Ireland, and South Africa (Strategic Consulting, 2009).

2.2.2.3. Donlen Corporation

Donlen claims to be the country's fastest-growing fleet leasing and management company (Donlen Brochure, 2009). The company, based out of Illinois, has 40 years of experience and has developed several in-house software solutions for its consulting operations. The Vehicle Optimization Model (VOM) provides comparative data for hundreds of vehicle types regarding fuel efficiency, cost per mile, emissions, vehicle replacement analysis, etc. The VOM also allows users to consider environmental impact as a key factor in their fleet management decisions. Additional proprietary Donlen tools include FleetWeb, which allows a user to analyze available data on the entire fleet, and a

Fleet Optimization Scorecard, which provides recommendations for the fleet (Donlen Brochure, 2009).

2.2.2.4. PHH Arval

PHH, the nation's second-largest provider of commercial fleet management services, provides a wide variety of fleet services to its clients, including accident management, financing, fuel management, new and used fleet vehicle sales, and regulatory services. The company also provides specialized services to managers of energy, utility, truck, and pharmaceutical fleets. Their focus is on saving the client money and increasing the productivity of both drivers and vehicles. While the company has a great deal of expertise in managing fleets, its level of management focuses more on the daily use of the vehicles as opposed to replacement analyses (About PHH Arval, 2009).

2.2.2.5. Wheels, Inc.

Wheels is a $2 billion company that manages more than 300,000 vehicles nationally. The majority of its clients are manufacturing and pharmaceutical fleets; only a small percentage is transportation and public utility clients. Wheels uses a proprietary analysis software called FleetView, which was released in 1999, to manage its fleets online. The company also developed Vehicle Replacement Optimization, which it bills as the market's first automated replacement analyzer (About Wheels, 2009).

2.3.3 State DOTs

Best practices of state DOTs are of particular interest to this study as DOT fleets are the most directly analogous to the fleet maintained by TxDOT. Table 2.1 below shows the ten largest state DOT fleets as reported by Automotive Fleet magazine. Several of these states are examined in further detail in the following sections. In addition to the descriptions below, Indiana, Maine, Minnesota, and Washington have all begun using FleetFocus fleet management software from Maximus (and now should be referred to as AssetWorks because Maximus had sold its fleet software business to AssetWorks several years ago (Maximus, 2006)).

Table 2.1: Top 10 State DOT Fleets

Rank	State	Vehicles
1	California	38,320
2	Florida	26,768
3	Texas	25,743
4	Georgia	19,691
5	New York	18,708
6	Pennsylvania	16,500
7	South Carolina	16,357
8	Virginia	15,823
9	Louisiana	13,000
9	New Jersey	13,000

Source: 2008-MY Statistics (2009)

2.2.3.1. California

According to AssetWorks, California makes use of their fleet management software (State Government, 2009). However, the University of California at Davis has also hired Mercury Associates in 2006 to provide technical assistance in researching best business practices and best technology solutions for managing fleet utilization (Mercury, 2009). The study's purpose was to make strategic recommendations to improve vehicle asset management for California state agencies and to lay the foundation for future fleet right-sizing (Fleet Management, 2007).

2.2.3.2. Florida

As of 2002, Florida used thresholds for mileage or age in order to determine vehicle replacement priorities. For example, full-size pickups are replaced at 8 years or 95,000 miles, dump trucks at 10 years or either 150,000 or 250,000 miles (depending on the capacity), hydraulic excavators at 8.000 hours or 12 years, and loaders at 10 years or 6,000 hours (Weissmann and Weissmann, 2002). In 2006, and 2007, Florida contracted with Mercury to evaluate its fleet management policies and practices.

2.2.3.3. Georgia

Georgia uses fleet management software from AssetWorks called FleetWorks (State of Georgia DOT, 2009). This program has been in use since 1998 and allows GDOT to carefully monitor its thousands of vehicles. Fleet management is carried out through GDOT's Office of Property and Equipment Management (Note: GDOT's website claims a fleet size of 8,600.)

2.2.3.4. Virginia

Over the past several years, Virginia Department of Transportation (VDOT) has contracted with Mercury to evaluate its fleet management and replacement methodologies (Mercury, 2009). Mercury assisted VDOT with the development of a fleet replacement planning and budgeting tool in 2005; today VDOT uses fleet management software by AssetWorks (State Government, 2009).

2.2.3.5. Oregon

Oregon's DOT fleet is being studied as part of an ongoing equipment replacement study through TRB. The study, entitled "Green and Economic Fleet Replacement Modeling," will analyze equipment cost and usage data in combination with emissions information to attempt to provide guidance to fleet managers on managing their fleets from an environmental perspective (2010-305, 2009).

Additionally, Oregon State University, working with ODOT, has completed a study intended to improve ODOT's existing fleet replacement model. The new model will be more accurate, more reliable, and more user-friendly (2010-305, 2009; Kim et al, 2009).

This study confirmed that most DOTs use fixed thresholds as a primary factor in equipment replacement decisions.

2.2.3.6. South Dakota

South Dakota is also undertaking a study on equipment replacement optimization; however, this study focuses on specific equipment types instead of being fleet-wide. In particular, South Dakota's DOT is concerned with roadway analysis equipment: video monitor, computer monitors and hardware, GPS units, etc. SDDOT is particularly concerned with the effect that technological change will have on their replacement decisions (Sendelweck, 2008).

2.2.3.7. Missouri

In 2007, Missouri's DOT chose the FASTER Fleet Management System, made by CCG Systems, Inc., for fleet and fuel management (Cable, 2007).

2.2.3.8. Arizona

Arizona uses FleetFocus fleet management software by AssetWorks. This software helps ADOT manage its 12,000 vehicle fleet.

2.3.4 Private Vehicle Management

AT&T currently has the largest fleet in the country with 86,099 vehicles. Ranking second is UPS with 72,633 vehicles, and third is Verizon with 64,888 vehicles (AT&T Bumps UPS, 2009).

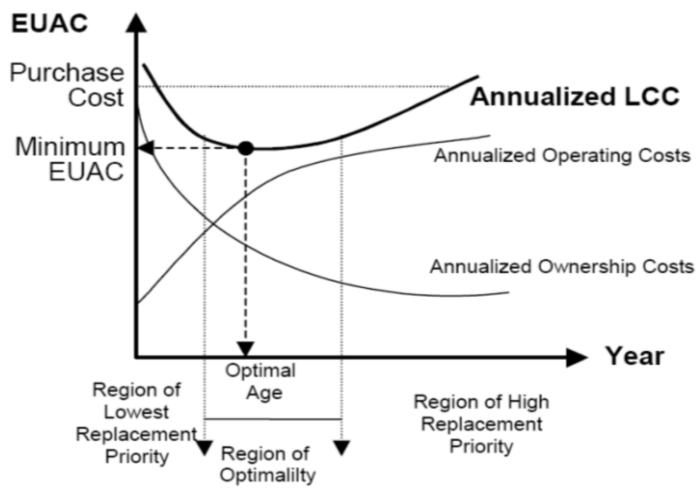
2.4 Existing ERO Research

The ERO problem deals with the determination of the replacement schedule so that the life cycle costs over the horizon can be minimized. In other words, ERO determines the age at which to sell the asset so that costs (purchase cost plus O&M cost minus salvage value) are minimized over the defined horizon. Much research has been done in the ERO area. Depending on the assumptions made under certain scenarios, the ERO problem can be classified into and solved by four categories from the solution approach perspectives, which are detailed as follows.

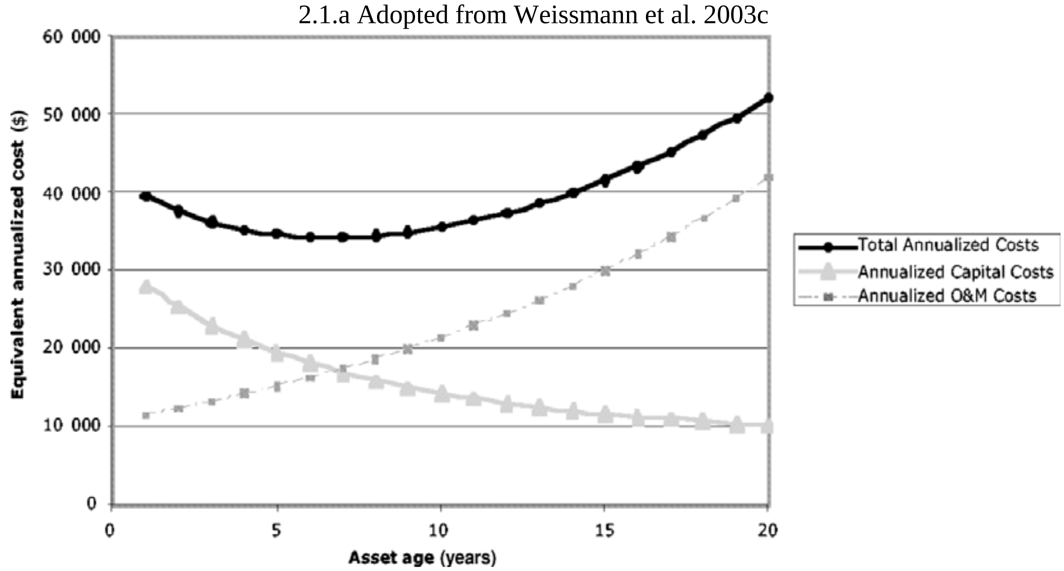
2.4.1 Minimum Equivalent Annual Cost (EAC) Approach

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. The economic life of an asset is the age which minimizes the Equivalent Annual Cost (EAC) of owning and operating the asset. This cost includes purchase and O&M costs less salvage values. To determine the EAC when retaining an asset for *n* periods, all costs over the *n* periods must be converted into *n* equal and economically equivalent cash flows using the interest rate. The economic life of an asset is typically computed by calculating the EAC of retaining an asset for each of its possible service lives, ages 1 through *N*, and the minimum is chosen from this set. In general, O&M costs rise with age whereas salvage values decline. Thus, the optimal solution trades off the high cost of replacement (purchase less salvage) versus increasing O&M costs over time. Once determined, the asset should be continuously replaced at this age under the assumption of repeatability and stationary costs (Hartman and Murphy, 2006).

This Minimum EAC method has been commonly presented in many engineering economy books (Grant et al, 1990). Several research efforts have been conducted on the ERO problem using this Minimum EAC method where the tradeoff between the annualized capital and operating costs is explicitly considered (Hartman, 2005; Hartman, 2008; Weissmann et al, 2003c; Hartman and Murphy, 2006; Gillespie and Hyde, 2004). The following Figure 2.1 illustrates the tradeoff that is considered in this Minimum EAC method between the annualized capital and operating costs.



2.1.a Adopted from Weissmann et al. 2003c



2.1.b Adopted from Hartman and Murphy, 2006

Figure 2.1: Annualized Purchase Cost, O&M Cost, and Total (EAC) Costs

2.4.2 Experience/Rule based Approach

As mentioned in section 2.2.1, TERM currently uses threshold values for age, use of an equipment unit, and repair cost as inputs for replacement (TERM, 2004). Also, in section 2.3, many other state DOTs use this experience/rule based approach to make keep/replacement decision for the equipment particularly during early stages. This experience/rule based approach to the ERO problem may work very well and can provide reliable keep/replacement decision for the fleet manager in some scenarios. However, this approach heavily depends upon the fleet manager's engineering judgment and experience with the ERO.

2.4.3 DDP 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 DDP approach is commonly used to solve the ERO problem.

There is an enormous amount of research on the ERO with finite time horizon using DDP (Hartman, 2005; Waddell, 1983; Hartman and Murphy, 2006, Bellman, 1995; Wagner, 1975). Furthermore, ERO in this case must make a decision about whether to replace or retain at each stage (typically annually) and this can be solved with two typical dynamic programming approaches, being Bellman's (Bellman, 1995) or Wagner's formulations (Wagner, 1975).

Bellman introduced the first DDP solution to the finite horizon equipment replacement problem where the age of the asset defines the state of the system with the decision to keep or replace the asset at the end of each period (stage). The formulation is presented by the network shown in Figure 2.2. In this network, each node represents the age 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) the asset. Keeping the asset connects nodes n and $n+1$ while replacing the asset nodes is shown by an arc connecting n and 1. An optimal policy with this model, in the form (K, K, R, K, K, …), gives the optimal decision in each period. It can be seen that if an asset can be retained for a maximum of N periods, then the maximum number of states in a period is N. For a T-period problem, since there are a maximum of two decisions for any state, so the problem can be solved in $O(2NT)$. Therefore, the computer complexity of Bellman's algorithm is $O(NT)$ (Bellman, 1955; Hartman, 2005; Hartman and Murphy, 2006).

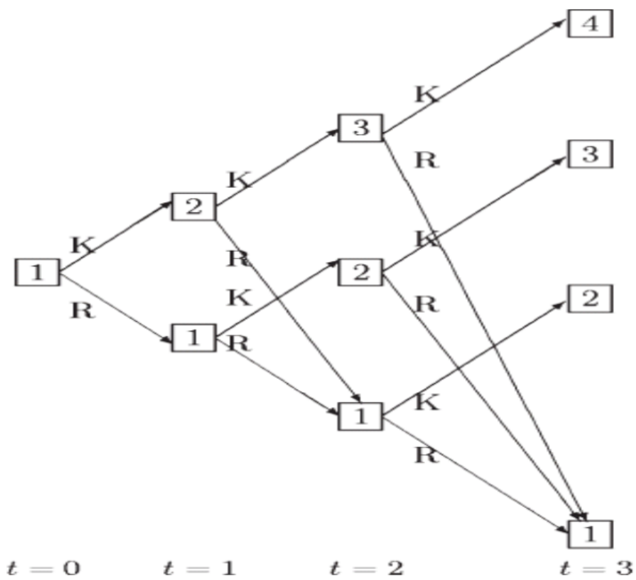


Figure 2.2: Network Representation of Bellman's Approach to the Equipment Replacement Problem

Wagner provided an alternative dynamic programming formulation to Bellman's solution in which the state of the system is the time period. In his approach, the decisions are the number of periods, 1, 2, . . . , *N* to retain an asset rather than whether to keep or replace the asset as shown in Bellman's approach. Let the value of *N* be again the maximum allowable service life for the asset. Figure 2.3 gives a network representation of Wagner's approach to the equipment replacement problem. In this network, each node represents the time period and each arc represents the amount of time that the asset is retained. If an arc connects nodes *t* and *t*+*n*, then it represents retaining an asset for *n* periods. The arcs are shown as *Kn*, meaning that the asset is to be kept for *n* periods. Since that there is a maximum of one state per period of time, *N* possible decisions for each state and *T* total periods, the problem can be solved in a computer complexity of O(*NT*) time, same as Bellman's approach. Furthermore, in Wagner's formulation, an optimal policy can be represented in the form of (n_1, n_2, n_3,. . .) in which each value of *n* denotes the number of periods an asset is retained. It can be clearly seen that the policies of the Bellman and Wagner formulations are equivalent in that they can be converted to each other. For example, the time n_1 in the Wagner model is equivalent to n_1 consecutive decisions of K followed by one of R, etc (Wagner, 1975; Hartman, 2005; Hartman and Murphy, 2006).

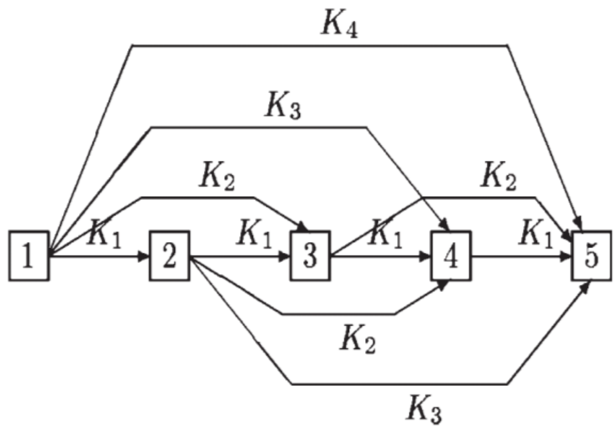


Figure 2.3: Network Representation of Wagner's Approach to the Equipment Replacement Problem

In addition, the DDP approach has been used to solve the ERO problem by few companies in the real world. For example, Waddell (Waddell, 1983) presented a model for the equipment replacement decisions and policies. It mentioned that a computer program using a DDP approach to optimize the projected discounted cash flow is used by the fleet managers at Phillips Petroleum Company for individual highway tractors as well as passenger cars and light trucks. Again, an annual cost savings of $90,000 was reported as the result of implementing this system for a fleet of 5300 vehicles.

2.4.4 SDP Approach

In the past, the main research study stream on the ERO problem is on using either the minimum EAC method or the DDP approach. The SDP approach is mainly used to solve the ERO problem with uncertainties and certainly this approach is problem specific and highly depends upon how the uncertainties are defined and studied. Meyer is one among very few to study the ERO problem under uncertainty perhaps due to computational constraints (Meyer, 1971). With the advances in computing technology, a lot of research efforts have examined the ERO problem under uncertainties during the past decade as can be seen by much of Hartman's research work.

As mentioned by Hartman (Hartman, 2008), there are numerous complications to the traditional ERO problem, which include, but are not limited to: 1) Multiple Assets; This is referred to as parallel replacement analysis where there is interdependence between budgets or economics (Hartman, 2004); 2) Uncertainty in Asset Utilization; The vehicle usage may not be pre-determined but actually random and depends on the operating environment (Hartman, 2001); 3) Uncertainty in Technological Change; How future challengers are modeled to capture the uncertainty in the technological change can be rather complicated (Bean et al, 1994; Hartman and Rogers, 2006; Hopp and Nair, 1991; Rogers and Hartman, 2005); 4) Uncertainty in the Time Horizon; and 5) Taxes (Hartman and Hartman, 2001).

In particular, ERO with multiple assets and ERO with taxes are the extended types of ERO problems. Usually, the DDP approach can be used and applied to solve these two types of problems. However, if the uncertainties are also considered for either of these two problem types, the problem will be very hard to solve and is therefore not generally studied in the ERO with uncertainty problem. In this regard, there are three types of ERO problems with uncertainties that have been investigated by Hartman (2008). The following gives a brief review on his research work:

2.4.4.1. ERO Problem with Uncertainty in Asset Utilization

Traditional deterministic economic replacement analysis optimizes asset purchase and sale decisions over a given horizon based on expected purchase, operating & maintenance, and salvage costs. As these costs are dependent on asset utilization, a constant or predetermined usage is generally assumed. However, due to randomness in real operations, these expected utilization schedules are normally not realized in practice, thus invalidating the replacement schedule under extreme conditions (Hartman, 2001).

Hartman (2001; 2004) investigated the ERO problem with uncertainty in asset utilization and examined the effect of probabilistic asset utilization on replacement decisions through the use of stochastic dynamic programming. In his research, the solution determines minimum expected cost decisions for each state defined by the asset's age and cumulative utilization in each period. These decisions generalize the definition of the economic life of an asset to include age and cumulative utilization. It is noted that assumptions common to replacement analysis allow the state space to grow linearly with time, avoiding dynamic programming's "curse of dimensionality". Examples with time invariant and variant economics were also presented and compared to traditional solution procedures. Figure 2.4 provides the SDP formulation with one challenger for the ERO problem with uncertainty in asset utilization.

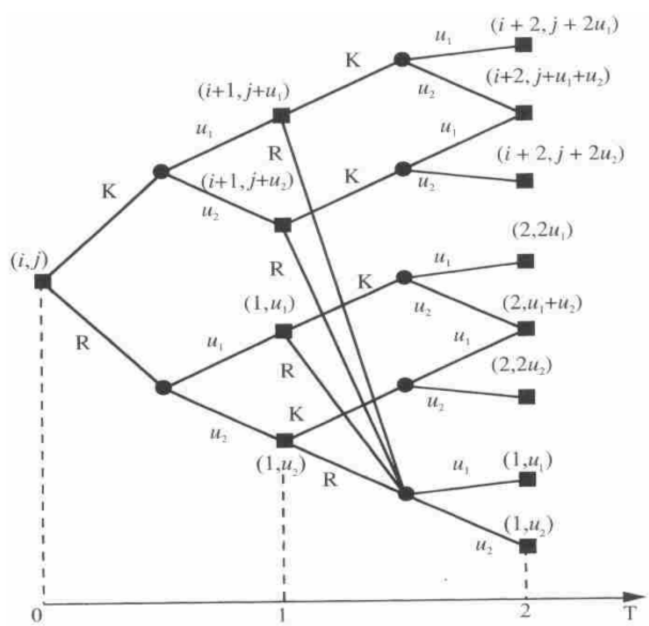


Figure 2.4: SDP Formulation with One Challenger for the ERO Problem with Uncertainty in Asset Utilization

In addition, Hartman (2008) presented some interesting scenario analysis and reduction techniques for the SDP formulation. It was also concluded that asset utilization could be included in traditional equipment replacement models without much computational difficulty.

2.4.4.2. ERO Problem with Uncertainty in Technological Change

Technological change is highly influential in equipment replacement problems and thus has been studied in great detail. Common assumptions include technological improvement at a continuous rate (Bean et al. 1994), according to a continuous function (Oakford et al. 1984), discontinuous technological change (Hopp and Nair 1991), or some combination (Rogers and Hartman 2005; Hartman and Rogers, 2006).

In particular, Hartman and Rogers developed and compared two dynamic programming formulations (i.e., Bellman's and Wagner's as presented in section 2.4.3) for cases including probabilistic technology breakthrough arrivals, probabilistic costs associated with breakthrough technologies and multiple challengers. It was found that although both the Bellman and Wagner methods can be extended to deal with realities such as technological change and multiple challengers, the Wagner method is better because these intricacies are more easily captured (Hartman and Rogers, 2006). For example, multiple challengers can be modeled by parallel arcs in the network connecting nodes between different time periods. Thus, preprocessing can eliminate inferior arcs before solving the problem. This is not possible with Bellman's formulation as the state space must be expanded to include the challenger type. Also, by analyzing the state space growth for each of these extensions under various parameter assumptions, Hartman and Rogers (2006) concluded that Wagner's method is more likely to succeed in solving large-scale problems (multiple challengers over long time horizons). Figure 2.5 gives a graphical decision network for the ERO problem with uncertainty in technological change.

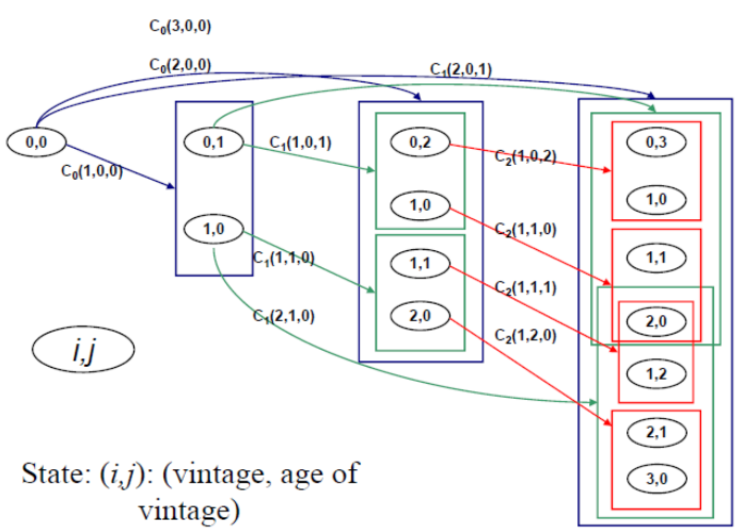


Figure 2.5: A Decision Network for the ERO Problem with Uncertainty in Technological Change (Adopted from Hartman, 2008)

It is noted that Hartman (2008) made some interesting economic implication conclusions, which included: 1) As the probability of new technology increases, length of time assets are retained decreases; and 2) Technological change generally induces faster replacement.

2.4.4.3. ERO Problem with Uncertainty in Horizon

Generally speaking, often equipment is only required for a finite length of time because 1) Equipment usage may be tied to a specific contract; and/or 2) Life of the service required may be finite. That is, the actual time required may be finite but uncertain because of uncertain production durations and/or temporary provision of service (Hartman, 2008). These situations might be compared to shortest path problems with uncertain distances (costs) or uncertain destinations (Hartman, 2008). In this case, the objective is still to minimize expected costs. However, many problems can exist when the horizon is finite but uncertain (Hartman, 2008).

2.5 Summary

A comprehensive review and synthesis of the current and historic research and development of the ERO problem, in both theoretical and practical applications, has been discussed in the preceding sections. This research is intended to provide a solid reference and assist in the model formulation and solution development of the ERO software. It also gives a clear picture of the current situation in fleet management worldwide and the direction ERO may take in the near future.

Chapter 3. Model Formulation

3.1 Introduction

As discussed in the literature review conducted in Chapter 2, the ERO 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. Section 2.4 provides a review of the literature on the existing ERO solution approaches. This chapter will formulate the ERO problem using the dynamic programming model.

The following sections are organized as follows. Section 3.2 provides some background information about the integer linear programming (ILP) model. Some general dynamic programming (including both DDP and SDP) characteristics will then be discussed in Section 3.3. Sections 3.4 and 3.5 present the detailed DDP and SDP model formulations respectively for the ERO problem. The mathematical notations and terminology used will be introduced in detail. Finally, section 3.6 concludes this chapter with a summary.

3.2 ILP Model

The ILP model involves minimization or maximization of a linear function subject to linear constraints where all the decision variables must take on integer values. Generally speaking, solving such models is non-deterministic polynomial-time hard (NP-hard) and computationally intractable, unless special problem structures exist. In other words, it generally will be very difficult to find the global optimal solution particularly when the problem to be solved becomes very large. Typical methods for solving small-medium sized ILP models and finding the global optimal solutions include the cutting-plane, branch and bound, branch and cut, and/or branch and price methods (Wolsey, 1998; Nemhauser and Wolsey, 1999). For large scale ILP models, heuristics or metaheuristics, (such as the local search, genetic algorithm, simulated annealing and tabu search methods) which can produce local optimal and possibly global optimal solutions within a reasonable amount of computational time, are commonly used to solve such NP-hard problems (Wolsey, 1998; Nemhauser and Wolsey, 1999). On the other hand, some NP-hard ILP optimization models may not be so computationally intractable and can be solved very efficiently regardless of the problem size when the problems have their own special problem structures. For example, ILP models having the total unimoularity characteristics can be solved using a relaxed linear programming (LP) approach to get the integer optimal solutions much faster. Other instances such as the well-known NP-hard knapsack problem can be solved by DP very efficiently (Wolsey, 1998; Nemhauser and Wolsey, 1999).

In particular, the ERO problem studied in this report has such special problem structures and can be formulated as an ILP model in which the objective is to minimize the total cost and the decisions to be made are to either replace or retain the unit of equipment at the beginning of each year. It should be noted that TxDOT fleet manager will replace the equipment unit at the end of each year if the optimal decision is to replace it at the beginning of that year --- This one year window allows sufficient time for the procurement and delivery of a new unit during that year. Previous research efforts have clearly indicated that the DP is the most efficient approach and can be effectively applied to solving the ERO problem (Hillier and Lieberman, 2005). The general DP characteristics and detailed DDP and SDP model formulations for the ERO problem are presented in the following sections.

3.3 General DP Characteristics

The basic features that characterize DP solution algorithms can be presented as follows (Hillier and Lieberman, 2005): 1) 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. 2) Each stage has a number of states associated with that stage. 3) 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). 4) 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. 5) Given the current state, the optimal policy decision for the remaining stages is independent of decisions made in previous states. 6) The solution procedure begins by finding the optimal policy for the last stage. 7) 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. 8) 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 (Wagner, 1975; Bertsekas and Tsitsiklis, 1996; Wolsey, 1998; Nemhauser and Wolsey, 1999; Bertsekas, 2001; Bellman, 2003; Denardo, 2003; Hillier and Lieberman, 2005).

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. SDP differs from DDP in that 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 (Bertsekas and Tsitsiklis, 1996; Bertsekas, 2001; Ross, 1995). 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.

As mentioned previously, the ERO problem studied in this report also has its own special problem structures and therefore, applying either DDP or SDP to solve the ERO problem requires particular attention to its unique structures and appropriate solution algorithms must be developed to cater to the ERO needs. In addition, it should be mentioned that the DDP-based optimization approach, which assumes that the annual purchase cost, annual operating & maintenance cost, salvage value, and the usage of the equipment unit are constant or predetermined and can be forecasted using historical data, is presented in section 3.4. (Fan et al, 2011b). However, due to uncertainty in real operations, these expected equipment utilization costs may not be realized, thus making the DDP decision sub optimal or worse under extreme conditions. In such cases, the SDP approach may be preferred. In this regard, the SDP approach is also developed and presented to solve the ERO problem in section 3.5.

3.4 DDP Model Formulation

Due to the abundance of research previously undertaken for DDP-based optimization and the complications involved in SDP-based optimization, this report first focuses on the DDP solution approaches assuming that the annual purchase cost, annual operating & maintenance cost, salvage value, and the usage of the equipment unit are constant or predetermined and can be forecasted using historical data (Fan et al, 2011b).

For the convenience of description, the DDP model formulation is organized in a systematic way and the following subsections present how to derive the optimal policy for the ERO problem using DP. The solution procedures are divided into three concrete steps: 1) Definition of appropriate stages and states; 2) Definition of the optimal-value function; and 3) Construction of a recursive computation relation.

3.4.1 Stages and States

Since the TxDOT fleet manager makes decisions as to whether to keep or replace a piece of equipment (based on the aggregated equipment's classcode) 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 referred to as the stage variable and the age of the equipment in service at the beginning of each year as the state variable.

For the convenience of presentation, the following mathematic notations are introduced:

Set/Indices/Input Variables

i_0 = the age of the unit of equipment at the starting stage

j_0 = the usage of the unit equipment (represented in mileage) at the starting stage

Y = the current year in which the unit of equipment is waiting for the keep/replacement decision at the starting stage

N = the user-specified maximum planning horizon for considering the keep/replacement decision

U_i = the usage (represented in mileage) of a unit of equipment during the decision year at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, ri_0 + N$.

C_i = the annual operating and maintenance (including downtime) cost of a unit of equipment during the decision year at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, ri_0 + N$.

P_k = the purchase cost of a new unit of equipment during year k, $k = Y, Y + 1, \dots 1Y + N - 1$.

S_{i,Y_0} = the salvage value of a unit of equipment during the decision year at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, \dots, i_0 + N$.

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 the procurement and delivery of a new unit of equipment. In addition, it should be noted that the model formulated is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles with or without budget considerations. In this regard, it is assumed that all the equipment must be salvaged at the end of the planning horizon of N years by the fleet manager if it is more than N years old. Furthermore, the value of the planning horizon N (i.e., the equipment maximum service life) is decided by the fleet manager. In this project, the TxDOT fleet manager highly recommended 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 as a result, the selection of the planning horizon N may have some impacts on the equipment optimal keep/replacement decisions. However, it is also believed that N=20 is a very reasonable value and is therefore highly recommended for the ERO problem for the State DOTs.

It can be seen from the above notations that the equipment purchase cost (P_k) is model year-based, the annual operating & maintenance cost (C_i) and the usage of the equipment unit (U_i) are both age-based, and that the salvage value (S_{i,Y_0}) is 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 (Fan et al, 2011a; 2011b) and act as inputs to the DDP-based optimization engine. Moreover, it is recognized 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 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) at each stage to be converted from the equipment model year (for the equipment purchase cost) and/or calendar year (for annual O&M costs and salvage value) to a benchmark year using the inflation rate. Such calculations of the discounting of future costs have been successfully performed (Fan et al, 2011b). Again, all equipment will be replaced at the end of the planning horizon of N years.

3.4.2 Optimal-Value Function

For any given pair of stage and state, the optimal-value function is defined as a function that returns the least total cost from that point to the end of the planning horizon. In particular, for the ERO problem, the optimal-value function is defined as follows:

$T_k^*(i) =$ minimal total cost from year k onward (through the end of year N), starting with an i-year-old equipment in year k.

3.4.3 Recursive Computation Relation

The ERO problem can be presented as follows: At the beginning of year k with an i-year-old equipment, the fleet manager has two available actions: either keep or replace. It should be noted again that the equipment will be used throughout that year k regardless of the decision being "keep" or "replace". Therefore, the annual operating and maintenance cost of that year is included as part of the costs under either decision scenario. The following presents both possible cases.

Case I: Suppose that the action chosen is to keep the i-year-old equipment. Then, the immediate one-stage cost is simply C_{i+1}. Since the next stage and state as a result of this action is $k+1$ and $i+1$, the minimal total future cost from that point to the end of the decision horizon is, by definition, $T_{k+1}^*(i+1)$. It therefore follows naturally that the best possible total cost associated with the keep action is given by $C_{i+1} + T_{k+1}^*(i+1)$.

Case II: Suppose that the action chosen is to replace the i-year-old equipment instead. Then, the immediate one-stage cost is the sum of: P_k (the purchase price of a new unit of equipment during the year k), $-S_{i+1,Y_0}$ (the negative of the revenue from the salvage value of the now

$(i+1)$-year-old equipment at the end of the decision year when the equipment is i-year-old at the beginning of the decision year), + C_{i+1} (the annual operating and maintenance cost of the now $(i+1)$-year-old equipment when ordering a new unit of equipment during that decision year). Since the next stage and state as a result of this action is $k+1$ and 0, the minimal total future cost from that point to the end of the decision horizon is, by definition, $T_{k+1}^{*}(0)$. It therefore follows that the best possible total cost associated with the replace action is given by $P_k - S_{i+1,Y_0} + C_{i+1} + T_{k+1}^{*}(0)$.

Since the goal of the ERO problem is to minimize the total cost, the recursive computation relation is presented as follows:

$$T_k^{*}(i) = \min\left[\, C_{i+1} + T_{k+1}^{*}(i+1),\ P_k - S_{i+1,Y_0} + C_{i+1} + T_{k+1}^{*}(0)\right].$$

With this recursive computation relation in place, the final step of the solution procedure consists of the recursive computation of the $T_k^{*}(i)$'s. By solving backwards, the ERO problem can potentially be solved efficiently and effectively using the DP approach.

The model formulation of the ERO problem has been discussed above. This is a typical DP-based ILP model. There has been an enormous amount of research on the ERO with finite time horizon using the DDP approach (Wagner, 1975; Bellman, 1995; Waddell, 1983; Hartman, 2005; Hartman and Murphy, 2006). However, it should be noted that almost all the previous research efforts are devoted to the DDP solution formulation and its limited applications to extremely simplified case studies and/or toy examples. The literature review indicates that there are very few research efforts made so far to apply such DDP approaches to solving the real world ERO problem. As a result, many underlying characteristics of the ERO problem are yet to be explored and identified. In this regard, the main contribution of this report is to develop a generalized DDP model and approaches for solving the real world ERO problems that are currently facing many State DOTs and many equipment fleets. Several characteristics underlying the ERO are presented and model results are generalized to make some very broad statements regarding ERO. Furthermore, the ERO software is developed to make a decision on whether to replace or retain equipment at the beginning of each year and this can be solved with the DP approach (either the Bellman or Wagner formulations).

3.5 SDP Model Formulation

As discussed in the above section 3.4, DDP optimizes the ERO decisions over a given horizon based on the expected purchase cost, annual O&M cost and salvage value. There has been an enormous amount of research on the ERO with finite time horizon using the DDP approach (Fan et al, 2011a; 2011b; Bellman, 1995; Bellman, 2003; Wagner, 1975; Waddell, 1983; Hartman, 2005; Hartman and Murphy, 2006). Reliable decisions can be produced and significant cost savings estimated by using the DDP approach using the real world data (Fan et al, 2011b, Waddell, 1983). However, there is an apparent shortcoming associated with this approach. For example, both the vehicle usage and the annual O&M cost are assumed to be constant or predetermined in DDP. Due to randomness in real operations, these expected equipment utilizations are normally not realized in practice, thus invalidating the replacement optimization decisions in some ways and making the DDP decision sub optimal or worse under extreme conditions (Fan et al, 2011c). In such cases, SDP, which can explicitly consider the uncertainty in the vehicle utilization and the annual O&M cost accordingly, will undoubtedly be the preferred approach to solving the ERO problem. Meyer is one among the very few to study the ERO problem under uncertainty perhaps due to computational constraints (Meyer, 1971). With the advances in computing technology, a lot of research effort has examined the ERO problem under uncertainties during the past decade as can be seen by much of Hartman's research work (Hartman and Rogers, 2006). However, none of these previous research efforts made uses the real world fleet cost/usage data and all previous case studies are limited and based on small examples. One will have reasonable doubts about whether the results presented were convincing or can be extended to real world applications. As a result, many underlying characteristics of the ERO SDP problem are yet to be explored and identified. An extensive review of the existing literature reveals that this is the first ERO SDP software that is targeted at the real world application (using TxDOT's current fleet data) and can explicitly consider the uncertainty in the vehicle utilization and the annual O&M cost. The pilot SDP-based work is very general and is intended to make some very broad statements regarding the ERO and can potentially be an example to demonstrate its promising feasibility. When enough cost/mileage data is collected, the SDP-based optimization solution can also be of immediate use and will yield substantial cost savings for years to come in the fleet management industry worldwide. To that end, the SDP model formulation and solution approaches are investigated in detail in this report. The basic structure for the SDP is provided in the following Figure 3.1.

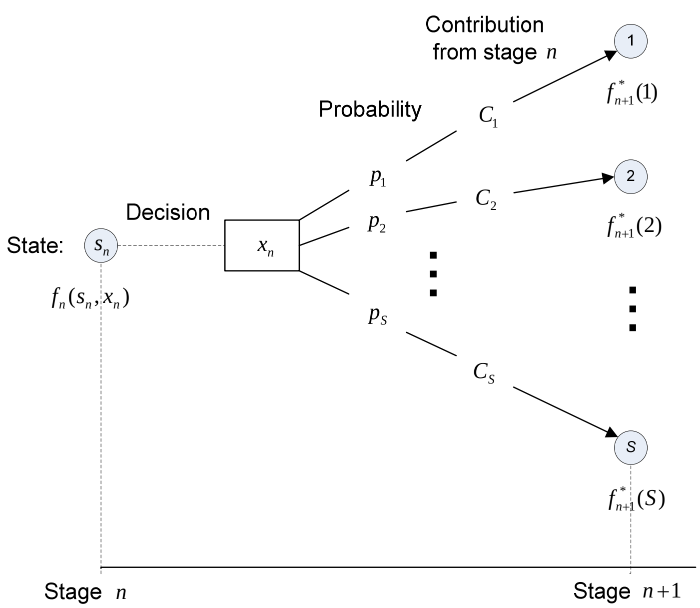


Figure 3.1: The Basic Structure for the SDP (Hillier and Lieberman, 2005)

For this illustration, let S represent the number of possible states at stage $n+1$ and label the states on the right as $1,2,\cdots,S$. Given state s_n and decision x_n at stage n the system goes to state i with probability $p_i (i=1,2,\cdots,S)$. If the system goes to state i, the contribution of stage n to the objective function is C_i.

Due to the probabilistic structure of SDP, the relationship between $f_n(s_n, x_n)$ and $f^*_{n+1}(s_{n+1})$ is certainly more complicated than that for the DDP. Since the objective of the ERO problem is to minimize the expected cost in this scenario by minimizing the expected sum of the contributions from the individual stages, let $f_n(s_n, x_n)$ denote the minimum expected sum from stage n onward, given that the state and policy decision at stage n are s_n and x_n, respectively. This results in the following equation.

$$f_n(s_n, x_n) = \sum_{i=1}^{S} p_i \left[C_i + f^*_{n+1}(i) \right]$$

with

$$f^*_{n+1}(i) = \min_{x_{n+1}} f_{n+1}(i, x_{n+1}),$$

where this minimization is taken over the feasible values of x_{n+1}.

For the convenience of description, the SDP model formulation is organized in a systematic way and the following subsections present how to derive the optimal policy for the ERO problem using DP. The solution procedures are detailed in the same manner as the DDP solution procedures (see section 3.4); there may be some repeated work in the following sections but it is necessary to sufficiently describe the SDP model formulation.

3.5.1 Stages and States

Again, 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 referred to as the stage variable and the age of the equipment in service and the level of cumulative utilization at the beginning of each year as the state variable.

For the convenience of presentation, the following mathematic notations are introduced:

Set/Indices/Input Variables

i_0 = the age of the unit of equipment at the starting stage.

j_0 = the usage of the unit equipment (represented in mileage) at the starting stage.

Y = the current year in which the unit of equipment is waiting for the keep/replacement decision at the starting stage.

N = the user-specified maximum planning horizon for considering the keep/replacement decision.

n_k = the number of possible utilization levels during year k, $k = Y, Y+1, Y+N-1$.

m_{t_k} = the average vehicle utilization (represented in mileage) for annual discretized level index t_k during year k, $t_k = 1, 2, \dots, n_k$, $k = Y, Y+1, \dots, Y+N-1$.

l_k = the realized mileage level used to represent the actual average vehicle utilization m_{t_k} during year k, $k = Y, Y+1, \dots, Y+N-1$.

U_{i,j,l_k} = the usage (represented in mileage) of a unit of equipment (with cumulative utilization j already at the beginning of the year) at level l_k during the decision year k at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, ri_0 + N$.

$p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right)$ = the probability of a unit of equipment being utilized at level l_{k+1} during the decision year $k+1$ at the end of which the equipment turns $(i+1)$-year-old given that it was utilized at level l_k during the decision year k at the end of which the equipment turns i-year-old.

C_{i,j,l_k} = the annual operating and maintenance (including downtime) cost of a unit of equipment (with cumulative utilization j already at the beginning of the year) at level l_k during the decision year k at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, ri_0 + N$.

P_k = the purchase cost of a new unit of equipment during year k, $k = Y, Y + 1, \dots 1Y + N - 1$.

S_{i,Y_0,j,l_k} = the salvage value of a unit of equipment (that was purchase at year Y_0 and with cumulative utilization j already at the beginning of the year) at level l_k during the decision year k at the end of which the equipment turns i-year-old, $i = i_0 + 1, i_0 + 2, ri_0 + N$.

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 the procurement and delivery of a new unit of equipment. Also, it is assumed that all the equipment must be salvaged at the end of the planning horizon of N years by the fleet manager if it is more than N years old. Furthermore, the value of the planning horizon N (i.e., the equipment maximum service life) is selected/decided by the fleet manager and the TxDOT fleet manager highly recommended a planning horizon of 20 years in this project by assuming that an equipment unit will be kept no longer than 20 years. Although it is expected that the selection/determination of the planning horizon N may have some impacts on the equipment optimal keep/replacement decisions, it is also believed that N=20 is a very reasonable value and is therefore highly recommended for the ERO problem for the State DOTs. It should also be noted that since all cost and vehicle utilization estimation and forecasting obtained from SAS macro are conducted with equipment age being up to 20 years for any equipment units at the classcode level, the 20-year-old forecast will be used whenever the equipment age exceeds 20.

It can be seen from the above notations that the equipment purchase cost (P_k) is model year-based. Both the annual operating & maintenance cost (C_{i,j,l_k}) and usage of the equipment unit (U_{i,j,l_k}) are both age-based and the probability distribution of the annual vehicle utilization level may depend on the cumulative mileage up to the decision year. The salvage value (S_{i,Y_0,j,l_k}) depends upon not only the model year and equipment age, but also the cumulative mileage at the time of disposal. As discussed in two preceding papers (Fan et al, 2011a; 2011c), all of this cost/mileage data and its probability distribution if any come from SAS as outputs of the SAS macro based data cleaner and analyzer, which will act as inputs to the SDP-based optimization engine. In addition, it should be noted that as a standard practice during the DP model and solution process, all such 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) at each stage have been converted from the equipment model year (for the equipment purchase cost) and/or calendar year (for annual O&M costs and salvage value) to a benchmark year using the inflation rate.

3.5.2 Optimal-Value Function

Again, for any given pair of stage and state, the optimal-value function is defined as a function that returns the least total cost from that point to the end of the planning horizon. In particular, for the ERO problem, the optimal-value function is defined as follows:

$T_k^*(i,j) =$ minimal total cost from year k onward (through the end of year N), starting with an i-year-old equipment with cumulative utilization j at the beginning of year k.

3.5.3 Recursive Computation Relation

Again, the ERO SDP problem can be presented as follows: At the beginning of year k with an i-year-old equipment with cumulative utilization j, the fleet manager has two available actions: either keep or replace. Note again that the equipment unit will be used throughout that year k regardless of the decision being “keep” or “replace”. Therefore, the annual operating and maintenance cost with the same probability distribution of that year is included as part of the costs under either decision scenario. The following presents both possible cases.

Case I: Suppose that the action chosen is to *keep* the i-year-old equipment with cumulative utilization j. Then, the immediate one-stage cost is simply C_{i,j,l_k} with probability $p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right)$, $l_k = m_1, m_2, \cdots m_{t_k}$. Since the next stage and state as a result of this action is $k+1$ and $i+1$ with cumulative utilization $j+l_k$, the minimal total future cost from that point to the end of the decision horizon is, by definition, $T_{k+1}^*(i+1, j+l_k)$. It therefore follows naturally that the best possible total cost associated with the *keep* action is given by $\sum_{l_k=m_1}^{l_k=m_{t_k}} p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right) * \left[C_{i,j,l_k} + T_{k+1}^*(i+1, j+l_k)\right]$.

Case II: Suppose that the action chosen is to *replace* the i-year-old equipment with cumulative utilization j instead. Then, the immediate one-stage cost is the sum of: P_k (the purchase price of a new unit of equipment during the year k), $-S_{i+1,Y_0,j+l_k,l_{k+1}}$ (the negative of the revenue from the salvage value of the now $(i+1)$-year-old equipment with cumulative utilization $j+l_k$ at the end of the decision year when the equipment is i-year-old with cumulative utilization j at the beginning of the decision year k), and C_{i,j,l_k} with probability $p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right)$, $l_k = m_1, m_2, \cdots m_{t_k}$ (the annual operating and maintenance cost of the now $(i+1)$-year-old equipment with cumulative utilization $j + l_k$ when ordering a new unit of equipment during that decision year). Since the next stage and state as a result of this action is $k+1$ and age 0 with mileage being 0, the minimal total future cost from that point to the end of the decision horizon is, by definition, $T_{k+1}^*(0,0)$. It therefore follows that the best possible total cost associated with the *replace* action is given by $P_k - S_{i+1,Y_0,j+l_k,l_{k+1}} + \sum_{l_k=m_1}^{l_k=m_{t_k}}\left[p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right) * C_{i,j,l_k}\right] + T_{k+1}^*(0,0)$.

Since the goal of the ERO problem is to minimize the total cost, the recursive computation relation is presented as follows:

$$T_k^*(i,j) = min\ \left\{\sum_{l_k=m_1}^{l_k=m_{t_k}} p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right) * \left[C_{i,j,l_k} + T_{k+1}^*(i+1, j+l_k)\right],\ P_k - S_{i+1,Y_0,j+l_k,l_{k+1}} + \sum_{l_k=m_1}^{l_k=m_{t_k}} \left[p\left(U_{i+1,j+l_k,l_{k+1}} \middle| U_{i,j,l_k}\right) * C_{i,j,l_k}\right] + T_{k+1}^*(0,0)\right\}.$$

With this recursive computation relation in place, the final step of the solution procedure consists of the recursive computation of the $T_k^*(i,j)$'s. By solving backwards using either Bellman's (Bellman, 1995; Bellman, 2003) or Wagner's formulations (Wagner, 1975), the ERO problem can potentially be solved efficiently and effectively using the SDP approach.

3.6 Summary

The general characteristics of ILP and dynamic programming models were presented in this chapter, along with a detailed discussion of both DDP and SDP model formulations. The model formulations provide a solid basis for the future overall solution methodology and the specific DP-based Bellman's and Wagner's solution approaches, which will be discussed in detail in the following chapters.

Chapter 4. Solution Methodology

4.1 Introduction

As mentioned before, the ERO problem involves minimizing total costs by making the decision to either keep or replace a unit of equipment at the beginning of each year. Chapter 3 discusses the DDP and SDP model formulations for the ERO problem. This chapter will present the DP-based solution methodology in detail.

The following sections are organized as follows. Section 4.2 provides a description of the general solution framework. Section 4.3 describes the Java-based graphical user interface (GUI). Section 4.4 discusses the SAS macro data cleaner and analyzer. Section 4.5 explains the DP-based optimization engine that runs the ERO software. Finally, section 4.6 concludes this chapter with a summary.

4.2 Solution Framework and its Distinct Features

Figure 4.1 provides a flow chart of the proposed solution framework for the ERO problem, which consists of three main components: 1) A Java based Graphical User Interface (GUI) that takes parameters selected by users, displays the final results of the optimization, and coordinates the other two components; 2) A SAS Macro based Data Cleaner and Analyzer, which undertakes the tasks of raw data reading, cleaning and analyzing, as well as cost estimation & forecasting; and 3) A DP-based optimization engine that minimizes the total cost over a defined horizon. These three components are briefly discussed in the following sections and more detailed discussions of each of the three components can be found in chapters 5, 6 and 7.

Again, this is the first ERO software that is targeted at the real world application (using TxDOT's current fleet data) and caters to TxDOT's own needs. However, it is believed that this pilot work is very general and may/can potentially be an example to demonstrate the promising feasibility and also immediate usability of the DP-based optimization solution, which can yield substantial cost savings for years to come in the fleet management industry worldwide.

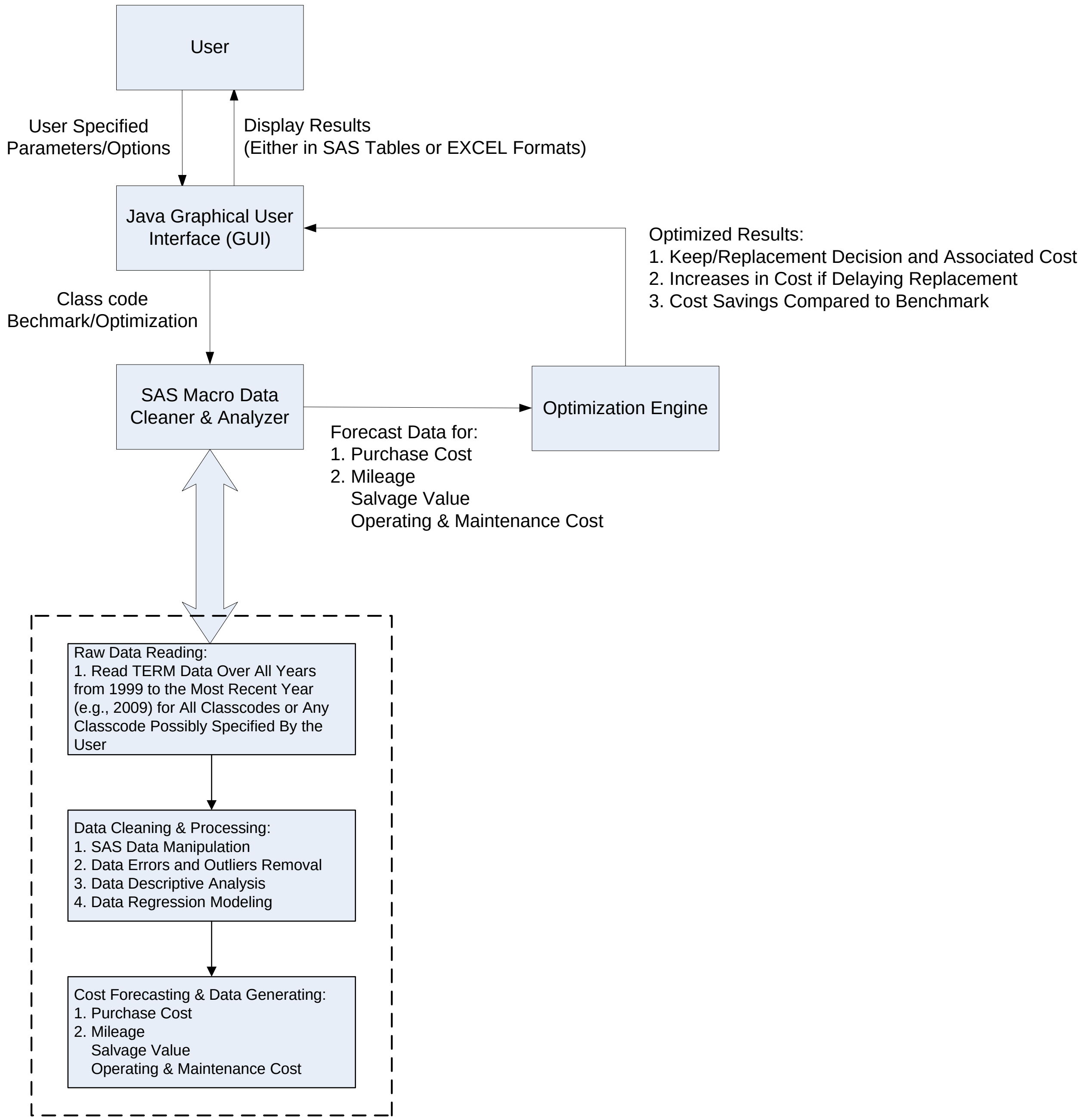


Figure 4.1: Flow Chart of the Developed ERO Solution Methodology

4.3 Java GUI

The Java GUI (which is written in Java code) has been developed to interact with the software users such as the fleet manager. It is designed to take the desired inputs from users and coordinate the SAS Macro Data Cleaner and Analyzer and the Optimization Engine. Once the optimization engine has made its decision, the results are presented to the software user (i.e., the fleet manager) either on screen or can be saved in EXCEL format through the GUI. A detailed examination of the specific characteristics and functionalities of the Java GUI will be provided in chapter 5.

4.4 SAS Macro Data Cleaner and Analyzer

When an optimization is run, the user specified options which are input through the Java GUI, are passed on to the SAS Macro Data Cleaner and Analyzer. The SAS macro codes are then executed to process the raw data corresponding to the user's inputs and his/her requirements. Raw TERM data is read and errors & outliers are removed, after which cost estimating, forecasting and data generating are performed. Several intermediate SAS tables are generated for the user's review, and several internal tables (some dealing with the classcode-level historic purchase cost data and future purchase cost forecasts, and the others containing the O&M cost, the salvage value, and the usage information for the classcode for each equipment age) are generated and passed on to the optimization engine. Further detailed information concerning the SAS Macro Data Cleaner and Analyzer and its data cleaning/analyzing procedures can be found in chapter 6.

4.5 DP-based Optimization Engine

Once the optimization engine (also written in Java code) receives the internal tables generated by the SAS macro codes it executes the DP-based optimization approaches and makes the best keep/replacement optimization decision. This decision is then passed on to the Java-based graphical user interface (GUI) for the users to review or save.

It should be noted that the proposed DP solution algorithms have been implemented and solved via backward recursion and Java based DP solution software is developed to minimize the total costs. The software developed can recommend an optimized solution whether to retain or replace a unit of equipment based on the equipment class, age, mileage, salvage value, and replacement cost from SAS macro codes. Additionally, the developed ERO solution methodology is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles both with and without annual budget considerations. In particular, knapsack programming optimization method will be used to solve the ERO problem under budget constraints in order to account for the optimal replacement of multiple equipment units. The Optimization Engine is further detailed in chapter 7.

4.6 Summary

The objective of this chapter is to present the basic framework of the ERO solution methodology and its three individual components. Major components designed, procedures followed, solution approaches developed, characteristics and functionalities of the ERO software development will be presented in detail in the following three chapters.

Chapter 5. Java GUI

5.1 Introduction

As discussed in Chapter 4, the first component of the ERO software is the Java GUI. This chapter provides a basic description of the functions incorporated and the options available to the user through the Java GUI.

The following sections are organized as follows. Section 5.2 describes how the Java GUI is organized. Section 5.3 lists the individual functions associated with the Java GUI. Finally, section 5.4 concludes this chapter with a summary.

5.2 Controllers and Views

The Java GUI in the developed software consists of two packages including the Controllers Package (class OptimizerController) and the Views Package (classes HomeView and OptionsView). The OptimizerController class is responsible for managing the entire program and acts as a delegate between GUI windows (views), the SAS macro codes, and the optimization engine, located in the optimizer package. This class should be run to execute the program. The HomeView class is the first view that is displayed when the OptimizerController is run. This class is responsible for getting input from the user and handling any actions performed on all GUI objects. Any non-GUI actions (such as saving preferences or running the engine) are handled by calling OptimizerController. The OptionsView class creates and displays a GUI window for program options. For example, one of the options available is SAS Install Location which specifies the location of the executable for running SAS (e.g., C:\Program Files\SAS\SAS 9.2\sas.exe). When saving options, the OptimizerController is called and it handles saving using preferences.

Figure 5.1 is a flow chart of the Java GUI OptimizerController package and provides a screenshot of the Java GUI in which the functionalities discussed in section 5.3 are incorporated. Figures 5.2 and 5.3 provide detailed flow charts for the OptimmizerController and HomeView respectively.

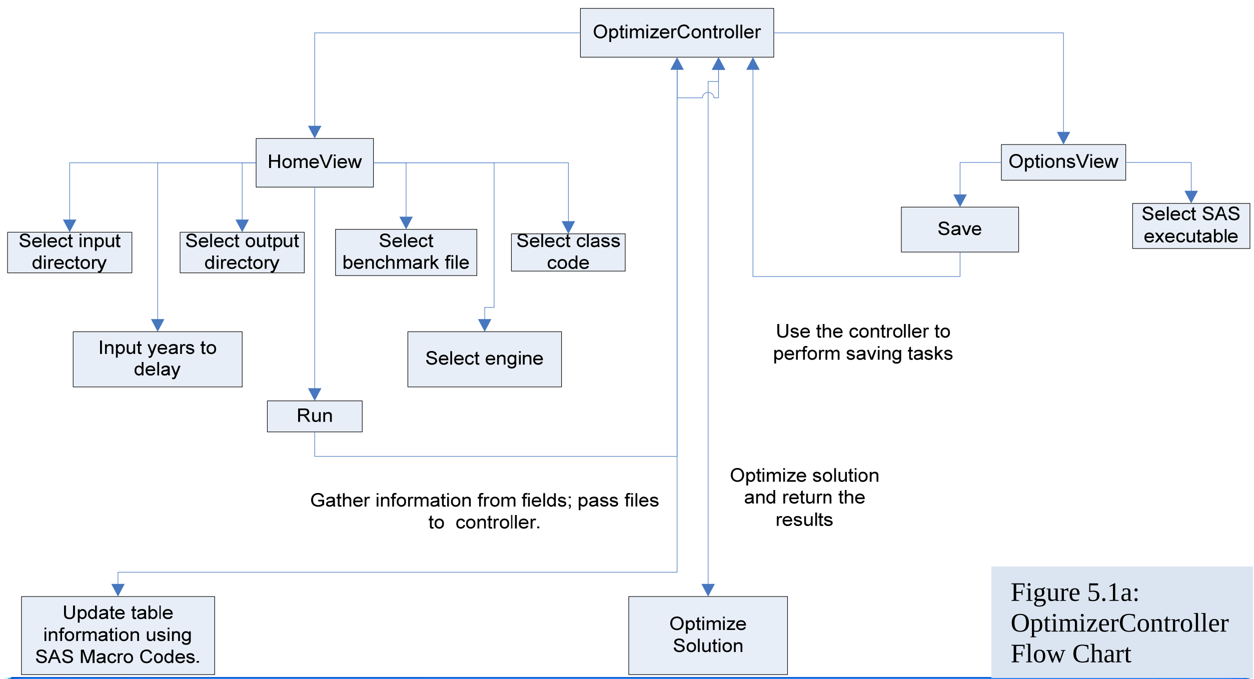


Figure 5.1a: OptimizerController Flow Chart

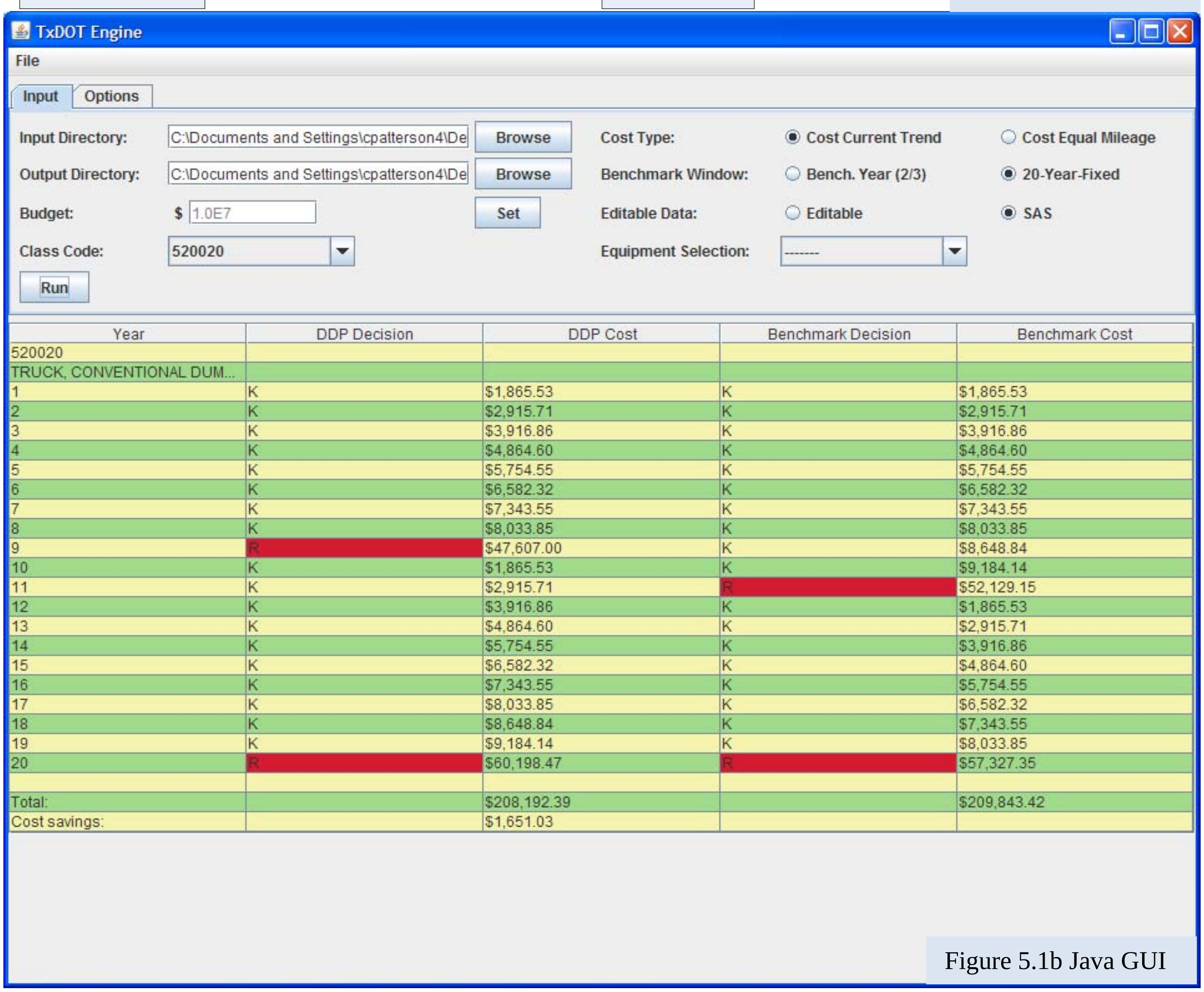


Figure 5.1b Java GUI

Figure 5.1: Flow Chart of the Java GUI OptimizerController and a Screenshot of the Java GUI

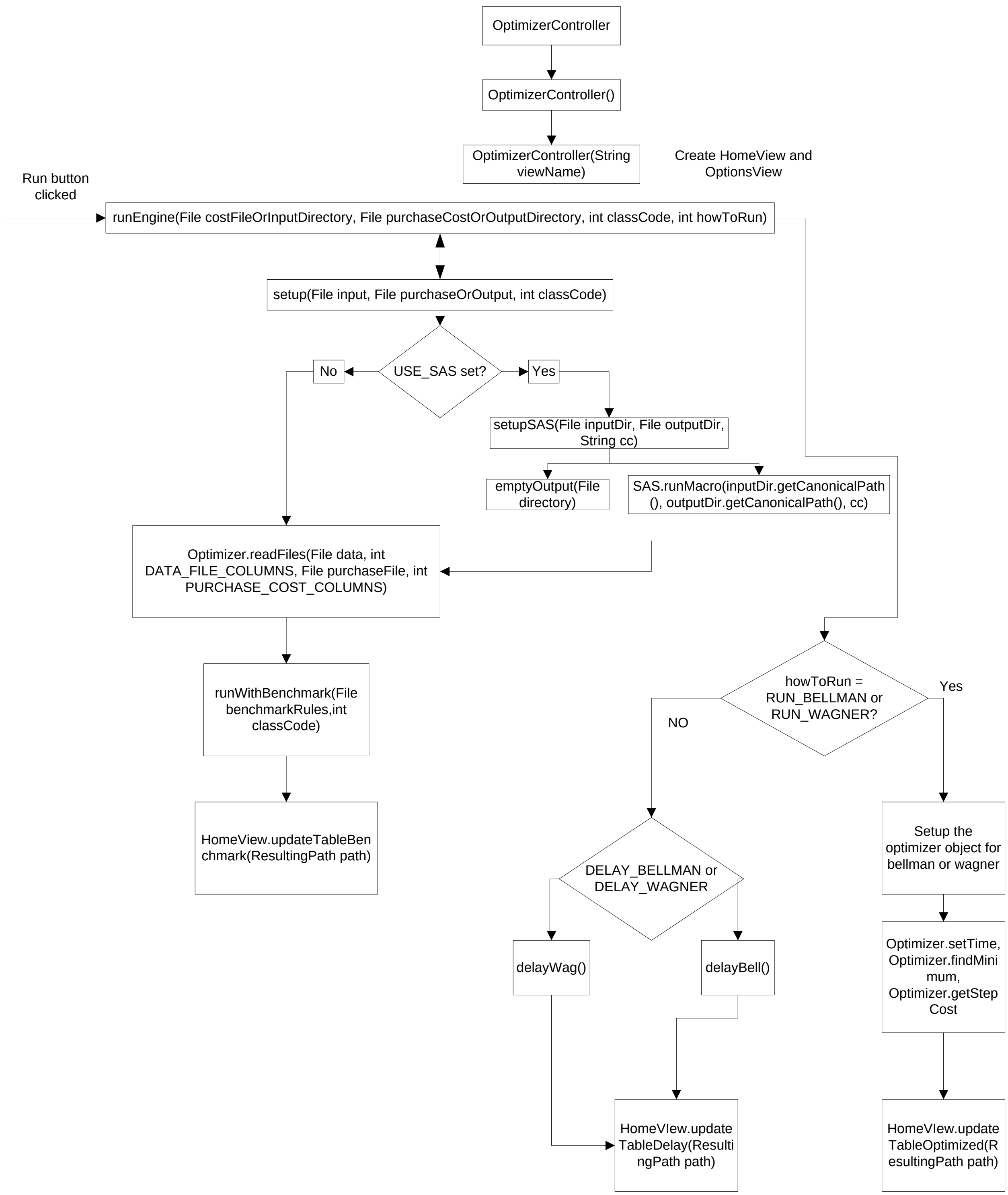


Figure 5.2: Flow Chart for the OptimizerController

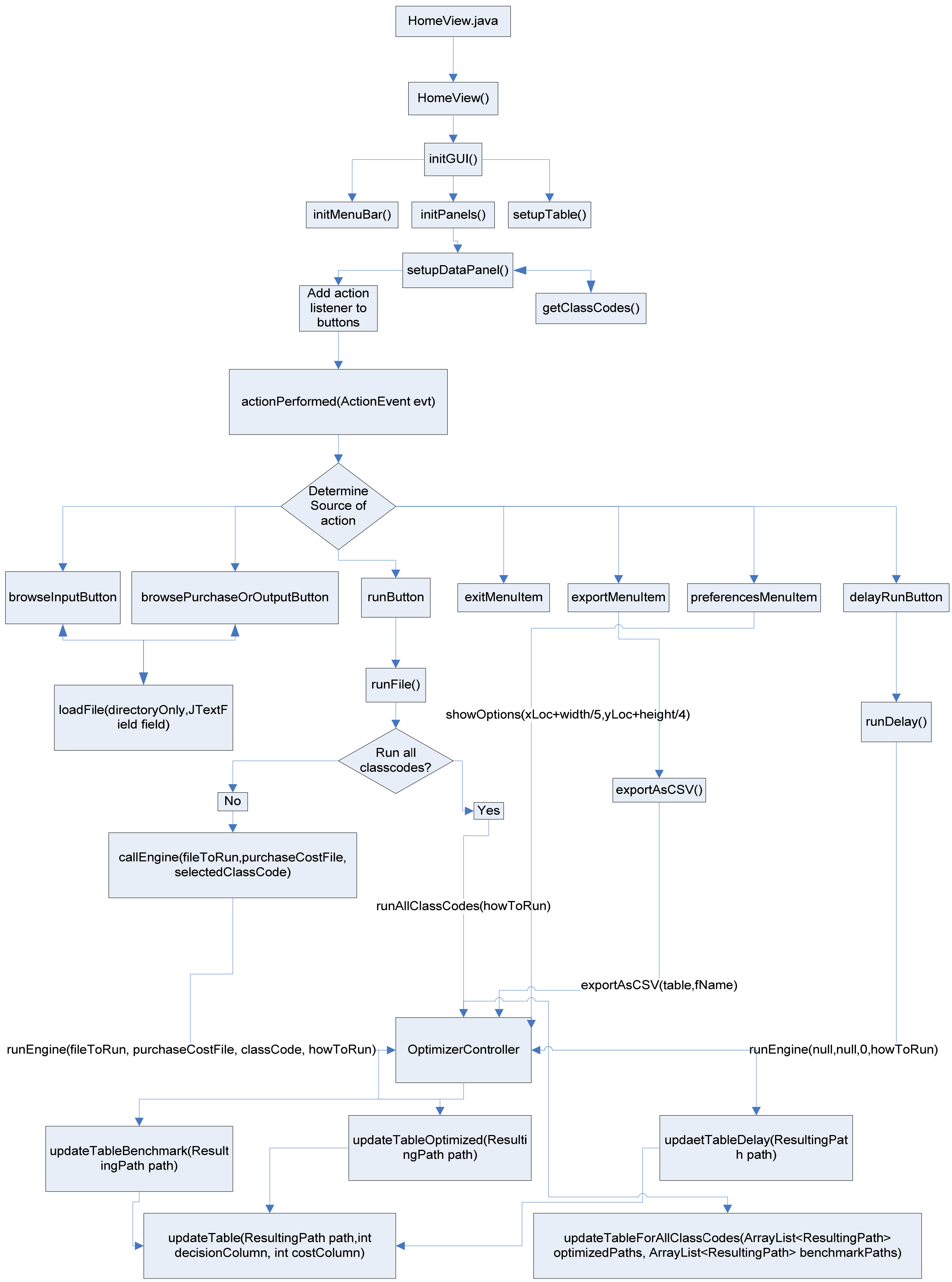


Figure 5.3: Flow Chart of the HomeView

5.3 Software Development and Functionalities

The Java-based GUI has been designed such that the user may easily select, from a variety of options, the exact parameters he/she wishes to use for optimization. These options are briefly described below, for more information on the different functions incorporated in this software please refer to the Product 1 (Practical Guidelines on ERO) in Appendix A.

- The user can choose to run optimization on either a single, specific classcode, or all classcodes for which there is available data.
- The user can specify to run optimization for a specific equipment unit, for brand new equipment units, or for all equipment units.
- The software allows the user to specify budget constraints.
- Two different approaches for forecasting cost and usage data are available (these are Cost Current Trend and Cost Equal Mileage).
    - “Current Trend” --- Takes all the information from current TERM data that are “error- and outlier- free” and assumes that the same trend will continue for all future years. For example, the current TERM data shows that equipment utilization decreases as equipment gets older and therefore it is assumed this trend will continue.
    - “Equal Utilization” --- Takes the average mileage across all equipment with same classcode and uses this number for the utilization for all equipment during that year. Note that the year-to-year utilization for the same classcode can still be different under this assumption.
- Optimization can be run with two different time windows; either the 20 year window suggested by TxDOT or the Benchmark year (2/3) option which only forecasts as far ahead as the next replacement.
- The user can choose to run the software using SAS automatically generated cost data or use the Editable cost data and make any changes to it as they might consider necessary and use such cost manually at the beginning of each year.
- The software gives the option to conduct the cost calculation by either Inflation Rate of by Cost of Money.
- The software allows users to selectively “Clean the data.”
- The user can choose from several different approaches, namely; DDP, SDP 2-Level, or SDP 3-Level; and Bellman or Wagner.
- The user can also choose to delay the replacement of equipment or replace it early by specifying a positive or negative delay time.
- 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 for the cost savings by comparing the optimal solution with the “delay by *N* years” option or “ignore the optimized decision” option (i.e. delay by 0 years).
- Finally, users can add new annual TERM data at the beginning of each year and make dynamic keep/replacement decisions for any chosen classcode or equipment units.

More details regarding the options available in the Java GUI can be found in the Product Report in Appendix A.

5.4 Summary

The Java GUI is discussed in this chapter, along with its detailed software functionalities. For a more detailed presentation of the input and other options and how to use them, please refer to the Product 1 (Practical Guidelines on Equipment Replacement Optimization) which can be found in Appendix A to this report.

Chapter 6. SAS Macro Data Cleaner and Analyzer

6.1 Introduction

The ERO is a truly complex problem and the current TxDOT TERM data contains extensive information that must be extracted and processed. The flow chart in Figure 6.1 also presents the sequence of the SAS macro codes, which implements and documents the comprehensive raw TERM data reading, cleaning, and processing, as well as the statistical modeling and cost forecasting processes.

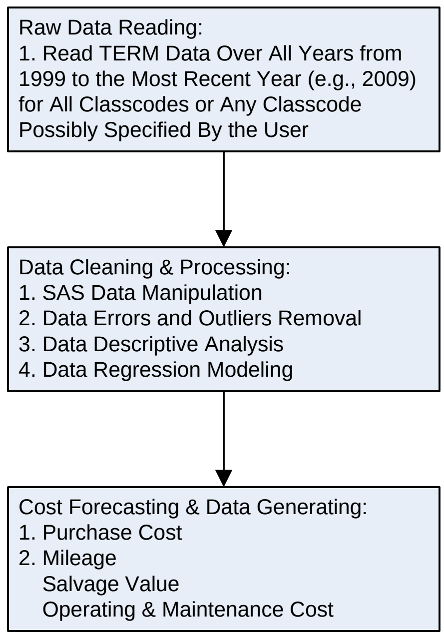


Figure 6.1: SAS Macro Flow Chart

The following sections are organized as follows. Section 6.2 describes how the SAS macro codes are used to read, clean, and process the TxDOT TERM data. Section 6.3 explains how the data forecasts are generated for the salvage values and the purchase costs. Finally, section 6.4 concludes this chapter with a summary.

6.2 Data Reading, Cleaning, and Processing

6.2.1 Raw Data Reading

As shown in the Figure 6.1, the first two steps are to read the raw data and to clean and process the data in the SAS macro data reader and analyzer. To accomplish this task, several source files written by the SAS macro codes are developed to read the TxDOT TERM raw data records from year 1999 to the most recent year (e.g., 2009). The specific steps taken during the data cleaning process are shown as follows: 1) Only records of "ACTIVE" equipment units are kept, which are equipment units with status not being "P" (purchase order processed), "Q" (requisitioned), "X" (retired equipment with payment pending); or "Z" (retired already); 2) Records with potential data errors (such as those with model year being zero) are identified, red-flagged and excluded from further analysis; 3) Records with exceptionally high and incomparable cost (e.g. if total purchase cost, the sum of the purchase cost and the net adjusted capital cost, is $9,484,823.00, it is deemed as exceptionally high for a single piece of equipment), such records are red-flagged and passed on to the later outlier treatments for possible removal. 4) If a piece of equipment has usage data for year zero, then this record is thrown out based upon advice from the project director. To further clarify this treatment, an example is provided as follows: Suppose in year 2003, the fleet manager ordered a piece of equipment whose model year is 2004 and used it for a short period of time during the 2003 year. Equipment age calculated using this equation (equipment age = current year – model year + 1) is 0, but the actual year of usage is 1. Since TxDOT uses model year (rather than the actual year of usage) to calculate the cost information for all datasets in any given year, to avoid confusion, such records are excluded from further analysis in the defined project scope.

6.2.2 Data Processing and Outlier Treatment

The current raw TxDOT TERM data, which includes age, miles (or hours) of operation, downtime, as well as O&M costs, has outliers in the variables. To get a quality result out of DP-based optimization solutions to the ERO problem, one needs to treat these outliers very carefully. Having realized the importance of proper outlier treatments, the state-of-the-art and state-of-the-practice outlier treatment techniques have been carefully reviewed. In order to ensure data quality, several advanced data cleaning and outlier treatment techniques have been explored and experiments are undertaken to remove all records with exceptionally low or high age, miles (or hours) of operation, downtime, as well as O&M costs. There are at least three approaches that can be used for outlier treatments (Fan et al, 2011a): 1) One relatively simple method is based upon the statistical confidence interval concept. That is, 95% of the data in a normally distributed distribution will lie within 1.96 standard deviates of the mean of the distribution. Therefore, one can treat any values more extreme than the mean plus and minus 1.96 standard deviates as outliers and discard them from analysis. Unfortunately, both the mean and the sample variance of a distribution (and therefore its standard deviation) suffer from the heavy influence of extreme values. As a result, using this rule-of-thumb does NOT always yield the desired result because the standard deviation is made too large by the very values that one would otherwise like to discard from the analysis (Shoemaker, 1999); 2) The second approach to outlier treatments is to use the median rather than the mean as the measure of central tendency; and 3) The third approach is to use an IQR (inter-quartile-range) computation. To accomplish the task, one must compute the inter-quartile-range (IQR) for continuous data and then take a multiple of it as a cut-off value to define values which are considered outliers. This method has been detailed in the work of Shoemaker (Shoemaker, 1999) as a very robust technique for identifying outliers: treat any value greater than the 75th percentile plus 1.5 times the inter-quartile distance, or less than the 25th percentile minus 1.5 times the inter-quartile distance as an outlier. According to many researchers, this technique was deemed as robust because it uses the quartile values instead of variance to describe the spread of the data and quartiles are less influenced by extreme values. Since this has been reported to be an extremely effective and widely used approach for outlier treatments, Shoemaker's IQR approach is used to treat the outliers of all cost/time variables. For example, some data records have exceptionally high total purchase cost (i.e., the sum of the purchase cost and the net adjusted capital cost) for a single piece of equipment and therefore are excluded for further analysis after the outlier treatments.

Note that solving the ERO problem using the dynamic programming approach requires all cost information (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) at each stage (i.e., decision year). It is necessary to convert all costs from the equipment model year (for the equipment purchase cost) and calendar year (for annual O&M costs and salvage value) to a benchmark year using the inflation rate (i.e., currently the benchmark is 2009 but the user can specify any year). The default adjustments are made based on the Consumer Price Index (CPI) inflation rate data published by U.S. Bureau of Labor Statistics (CPI Inflation Calculator, Bureau of Labor Statistics, 2009).

The following Table 6.1 provides a summary of the number of records (by year) obtained including the current TxDOT TERM raw data records, the active equipment records, total records after removing data errors, and total records after outlier treatments. As one can see, active equipment records consist of an average of 86% of the raw data and only about 0.2% of them have errors. Out of all error-free active records, approximately 27% have outliers. Overall, the number of active records deleted (either having outliers or with errors) accounts for 27.3 percent of all active equipment records. This is not a small fraction and it is therefore expected that this outlier treatment process will significantly improve the quality and reliability of the later cost estimation and data forecasting.

Table 6.1: Yearly Records Obtained during the Data Cleaning Process

Year	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Total Records	20368	19992	20335	19714	20152	20192	20973	21336	21378	20191	19147
Active Equipment Records	17188	17209	17472	17317	17187	17759	17779	18072	17900	17046	16415
Total Records After Removing Errors	17126	17174	17443	17283	17157	17733	17752	17998	17833	17020	16370
Total Records After Removing Outliers	12288	12374	12647	12651	12465	12876	12954	12895	13049	12590	12222

During the process of SAS macro data cleaning and analyzing as well as cost data forecasting & generating, all produced SAS datasets are kept as intermediate tables in case the fleet manager or software users wish to examine these intermediate tables to see whether the data cleaning process has been performed in a reasonable way. Also, these tables can serve as roadmaps for internal software developing and testing purposes.

6.3 Cost Forecasting and Data Generating

As part of the SAS macro data cleaner and analyzer, several salvage value calculations and data forecasting methods are also carefully examined. Several advanced linear and nonlinear mathematical models have been developed and a series of regression analyses are conducted to ensure data forecasting quality. After conducting numerous cost modeling experiments and comprehensive DDP solution tests, there has been enough evidence to indicate that all data forecasting, in particular the salvage value, downtime cost and the purchase cost forecasting, are very important factors for the ERO problem and can have a truly significant impact on the ERO keep/replace decision. Correctly forecasting the salvage value and other costs is extremely important to the ERO problem because they are used at each stage and are associated with each replace/keep decision. The following two subsections will present the salvage value calculation and purchase cost calculation in detail.

6.3.1 Salvage Value Calculation

In this report the development of a more robust salvage value estimation model for both heavy and light vehicles has been experimented with. The development process for each of these models is described below.

For heavy vehicles, the salvage value analysis completed by Lucko (Lucko, 2003) is used. In this analysis, Lucko provides ratios for salvage values as compared to original purchase prices for several vehicle types at ages zero to fifteen years. Specifically, Lucko looked at 11 different equipment types and 28 categories by size as measured by horse power, standard operating weight, or bucket volume. Lucko's analysis looks at four vehicle manufacturers: Caterpillar, Deere, Komatsu, and Volvo. Each of these four does not produce all of the 28 types of vehicles, but for vehicles produced by more than one manufacturer, salvage values are similar between manufacturers. Therefore, because Caterpillar has the most complete set of salvage values, these values have been chosen to be the salvage value model used in this project. The exception is for Track Dozers (0-99 HP), for which Komatsu data was used because Caterpillar does not manufacture a track dozer of this size.

In describing the analyzed vehicle types, Lucko states: "The equipment types studied are hydraulic excavators (track-type, wheel-type), loaders (wheel-type, track-type, backhoes, integrated toolcarriers), rear-dump haulers (rigid frame, articulated), track dozers, motor graders, and wheel tractor scrapers. Rare or specialty types of equipment like cranes, rollers, and trenching and boring machines were not considered." For the salvage value models, careful judgment has been used to match Lucko's vehicle types with those defined by TxDOT. Not all of the TxDOT vehicle types have a corresponding Lucko vehicle type. A table of heavy vehicle comparisons and a table of heavy vehicle salvage value ratios are provided below.

Table 6.2: Heavy Vehicle Type Comparisons

TxDOT Class Code	TxDOT Vehicle Type	Lucko Vehicle Type
1010	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, TO 29', INC TRUCK	Rigid-Frame Truck (0-99,999 lbs)
1020	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 30-39', INC TRUCK	Rigid-Frame Truck (0-99,999 lbs)
1030	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 40-59', INC TRUCK	Rigid-Frame Truck (0-99,999 lbs)
1040	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 60' +, INC TRUCK	Rigid-Frame Truck (0-99,999 lbs)
1050	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, MILEAGE	Rigid-Frame Truck (0-99,999 lbs)
11010	ASPHALT DISTRIBUTOR, TRUCK MOUNTED, (INCLUDES TRUCK)	Rigid-Frame Truck (0-99,999 lbs)
12010	ASPHALT MAINTENANCE UNIT, 600 GAL, TRAILER MOUNTED	Rigid-Frame Truck (0-99,999 lbs)
12020	ASPHALT MAINTENANCE UNIT, 1000 GAL, TRAILER MOUNTED	Rigid-Frame Truck (100,000+ lbs)
12030	ASPHALT MAINTENANCE UNIT, TRUCK MOUNTED	Rigid-Frame Truck (0-99,999 lbs)
12040	ASPHALT MAINTENANCE UNIT, DUMPBODY CONTAINED	Rigid-Frame Truck (0-99,999 lbs)
14000	ASPHALT MELTING KETTLE (HTR), TRAILER MOUNTED	Rigid-Frame Truck (100,000+ lbs)
19000	ASPHALT RECLAIMER/STABILIZER, CLASS I, SP, < 94.5 CUT WIDTH	Rigid-Frame Truck (100,000+ lbs)
44000	EARTH BORING MACHINE, TRUCK MOUNTED (INCLUDES TRUCK)	Rigid-Frame Truck (100,000+ lbs)
52010	CRANE, CARRIER MOUNTED, CABLE OR TELESCOPING	NA
52020	CRANE, CRAWLER TYPE, CABLE CONTROL	NA
54000	CRANE, TELESCOPING BOOM, TRUCK MOUNTED (INCLUDES TRUCK)	Rigid-Frame Truck (0-99,999 lbs)
56000	CRANE, YARD/INDUSTRIAL, SELF PROPELLED	NA
64000	DYNAMIC DEFLECTION SYSTEM, TRAILER MOUNTED	Rigid-Frame Truck (0-99,999 lbs)
70010	EXCAVATOR, HINGED OR TELESCOPING BOOM, CRAWLER TYPE	Track Excavator (25,000-49,999 lbs)
70020	EXCAVATOR, HINGED BOOM, PNEUMATIC TIRED CARRIER	Track Excavator (25,000-49,999 lbs)
75010	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS I	Track Excavator (25,000-49,999 lbs)
75020	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS II	Track Excavator (25,000-49,999 lbs)
75030	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS III	Track Excavator (25,000-49,999 lbs)
80000	FORKLIFT, ELECTRIC	Wheel Loader (0-1.9 CY)
85010	FORKLIFT, ENGINE DRIVEN, UP TO 3,999 LB CAPACITY	Wheel Loader (0-1.9 CY)
85020	FORKLIFT, ENGINE DRIVEN, 4,000 LB AND OVER CAPACITY	Wheel Loader (2-3.9 CY)
90010	GRADER, MOTOR, CLASS I, UP TO 109 H.P.	Motor Grader (0-149 HP)
90020	GRADER, MOTOR, CLASS II, 110-134 H.P.	Motor Grader (0-149 HP)
90030	GRADER, MOTOR, CLASS III, 135-149 H.P.	Motor Grader (0-149 HP)
90040	GRADER, MOTOR, CLASS IV, 150 H.P. AND GREATER	Motor Grader (150+ HP)
110010	LOADER, CRAWLER, UP TO 1.9 CU.YD. CAPACITY	Track Loader (0-1.9 CY)
110020	LOADER, CRAWLER, 2 CU. YD. CAPACITY AND GREATER	Track Loader (2+ CY)
115000	LOADER, PNEUMATIC TIRED, SKID STEER	Wheel Loader (0-1.9 CY)
115010	LOADER, PNEUMATIC TIRED, UP TO 1 1/2 CY	Wheel Loader (0-1.9 CY)
115020	LOADER, PNEUMATIC TIRED, 1 1/2 CY	Wheel Loader (0-1.9 CY)
115030	LOADER, PNEUMATIC TIRED, 2 CY	Wheel Loader (2-3.9 CY)
115040	LOADER, PNEUMATIC TIRED, 2 1/2 AND 3 CY	Wheel Loader (2-3.9 CY)
132040	MOWER, TRAIL TYPE, ROTARY, 9 FT AND GREATER	NA
136010	MOWER, SLOPE, SIDE BOOM, TRACTOR MOUNTED, INC TRACTOR	NA
140040	PAINT STRIPE MACHINE, 2 COLOR, MULTI-LINE, TRUCK MOUNTED	Rigid-Frame Truck (0-99,999 lbs)
154000	PAVEMENT PROFILING MACHINE, SELF PROPELLED	Rigid-Frame Truck (100,000+ lbs)
156010	PAVER, BITUMINOUS, SELF PROPELLED	Rigid-Frame Truck (100,000+ lbs)
162020	PULVERIZER-MIXER, EARTH, SELF PROPELLED	Rigid-Frame Truck (100,000+ lbs)
170010	ROLLER, FLATWHEEL, SELF PROPELLED 4-6 TON W/PNMTC TRS	NA
170020	ROLLER, FLATWHEEL, SELF PROPELLED 5-8 TON	NA

Table 6.3: Heavy Vehicle Type Comparisons Cont.

TxDOT Class Code	TxDOT Vehicle Type	Lucko Vehicle Type
170030	ROLLER, FLATWHEEL, SELF PROPELLED 8-14 TON	NA
174010	ROLLER, PNEUMATIC TIRED, SELF PROPELLED	NA
176010	ROLLER, TAMPING, SELF PROPELLED	NA
178010	ROLLER, VIBRATING, SELF PROPELLED	NA
178020	ROLLER, VIBRATING, SELF PROPELLED W/PNEUMATIC TIRES	NA
186000	SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED	NA
186010	SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED, SOLAR PWRED	NA
192010	SPRAYER, HERBICIDE/INSECTICIDE, TRUCK MOUNTED (INC TRK)	Articulated Truck (0-49,999 lbs)
194010	SPREADER, AGGREGATE, SELF POWERED	NA
202010	SWEEPER, ROAD, SELF PROPELLED	Articulated Truck (0-49,999 lbs)
204020	SWEEPER, STREET, TRUCK MOUNTED	NA
204030	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, UP TO 5.9 CY	NA
204040	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, 6 CY & UP	NA
214000	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, MILEAGE	Articulated Truck (0-49,999 lbs)
214010	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, HOURLY	Articulated Truck (0-49,999 lbs)
220010	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) TO 100 HP	Track Dozer (0-99 HP)
220020	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 100-129 HP	Track Dozer (100-199 HP)
220030	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 130-179 HP	Track Dozer (100-199 HP)
230010	TRACTOR, PNEUMATIC TIRED, TO 49 HP (TRACTOR ONLY)	Wheel Loader (0-1.9 CY)
230020	TRACTOR, PNEUMATIC TIRED, 50-64 HP (TRACTOR ONLY)	Wheel Loader (2-3.9 CY)
230030	TRACTOR, PNEUMATIC TIRED, 65 HP & GREATER (TRACTOR ONLY)	Wheel Loader (2-3.9 CY)
240020	TRACTOR, PNEUMATIC TIRED, W/LOADER & BACKHOE, TO 60 HP	Backhoe Loader (0-0.9 CY)
240030	TRACTOR, PNEUMATIC TIRED, W/LOADER AND BACKHOE, 60 HP & UP	Backhoe Loader (1+ CY)
260010	TRAILER, EQUIPMENT, TILT BED/UTILITY, TO 24,000 LB CAPACITY	Articulated Truck (0-49,999 lbs)
260020	TRAILER, EQUIPMENT, TILT BED/UTILITY, 24,000 LB CAP & GREATER	Articulated Truck (0-49,999 lbs)
260030	TRAILER, EQUIPMENT, GOOSENECK	Articulated Truck (0-49,999 lbs)
280010	TRAILER, TRANSPORT, PLATFORM	Articulated Truck (0-49,999 lbs)
280020	TRAILER, TRANSPORT, SIGN	Articulated Truck (0-49,999 lbs)
480010	TRUCK, PLTFM, PLTFM DUMP, STAKE, 8600-14999 GVWR	Articulated Truck (0-49,999 lbs)
490010	TRUCK, LIGHT/MEDIUM, 14,500 TO 18,999 GVWR	Articulated Truck (0-49,999 lbs)
500010	TRUCK, ALL BODY STYLES, 15,000-18,900 GVWR	Articulated Truck (0-49,999 lbs)
510010	TRUCK, ALL BODY STYLES, 19,000-20,900 GVWR	Articulated Truck (0-49,999 lbs)
520010	TRUCK, ALL BODY STYLES EXC CONV DUMP, 21000-25400 GVWR	Articulated Truck (0-49,999 lbs)
520020	TRUCK, CONVENTIONAL DUMP, 21000-25400 GVWR	Articulated Truck (0-49,999 lbs)
520030	TRUCK, EJECTION TYPE MATERIAL BODY, 21000-25400 GVWR	Articulated Truck (0-49,999 lbs)
530010	TRUCK, ALL BODY STYLES, EXC CONV DUMP/WRKR 25500-28900	Articulated Truck (0-49,999 lbs)
530020	TRUCK, CONVENTIONAL DUMP, 25500-28900 GVWR	Articulated Truck (0-49,999 lbs)
530030	TRUCK, EJECTION TYPE MATERIAL BODY, 25500-38900	Articulated Truck (0-49,999 lbs)
540010	TRUCK, DUMP, SINGLE REAR AXLE,29000-42900 GVWR	Articulated Truck (0-49,999 lbs)
540020	TRUCK, DUMP, TANDEM REAR AXLE, 43000 GVWR AND GREATER	Articulated Truck (50,000+ lbs)
550010	TRUCK, ALL STYLES EXC DUMP, SINGLE REAR AXLE 29000-38900	Articulated Truck (0-49,999 lbs)
550020	TRUCK, ALL STYLES EXC DUMP, TANDEM REAR AXLE 39000 +	Articulated Truck (0-49,999 lbs)
600010	TRUCK TRACTOR, SINGLE REAR AXLE, UP TO 60000 GCWR	Articulated Truck (50,000+ lbs)
600020	TRUCK TRACTOR, SINGLE REAR AXLE, 60000 GCWR & GREATER	Articulated Truck (50,000+ lbs)
600030	TRUCK TRACTOR, TANDEM REAR AXLE, ALL GCWR	Articulated Truck (50,000+ lbs)

Table 6.4 Heavy Vehicle Salvage Value Ratios

Years of Age	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Track Excavator (0-24,999 lbs)	0.6477	0.5682	0.4962	0.4317	0.3746	0.3251	0.2830	0.2484	0.2213	0.2016	0.1895	0.1848	0.1848	0.1848	0.1848	0.1848
Track Excavator (25,000-49,999 lbs)	0.5494	0.4998	0.4543	0.4128	0.3754	0.3419	0.3125	0.2871	0.2657	0.2483	0.2350	0.2256	0.2203	0.2190	0.2190	0.2190
Track Excavator (50,000-74,999 lbs)	0.5188	0.4521	0.3919	0.3381	0.2908	0.2500	0.2157	0.1878	0.1664	0.1515	0.1431	0.1412	0.1412	0.1412	0.1412	0.1412
Track Excavator (75,000-99,999 lbs)	0.5820	0.5037	0.4328	0.3693	0.3131	0.2643	0.2228	0.1887	0.1620	0.1426	0.1306	0.1259	0.1259	0.1259	0.1259	0.1259
Track Excavator (100,000+ lbs)	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Wheel Excavator (All Sizes)	0.6367	0.5658	0.5010	0.4421	0.3893	0.3426	0.3019	0.2672	0.2386	0.2160	0.1994	0.1889	0.1845	0.1845	0.1845	0.1845
Wheel Loader (0-1.9 CY)	0.5249	0.4899	0.4570	0.4260	0.3971	0.3702	0.3452	0.3223	0.3013	0.2824	0.2655	0.2505	0.2376	0.2266	0.2177	0.2108
Wheel Loader (2-3.9 CY)	0.6565	0.5939	0.5363	0.4835	0.4356	0.3925	0.3543	0.3209	0.2925	0.2688	0.2501	0.2361	0.2271	0.2229	0.2229	0.2229
Wheel Loader (4-5.9 CY)	0.6270	0.5659	0.5099	0.4590	0.4132	0.3725	0.3368	0.3062	0.2807	0.2603	0.2450	0.2347	0.2295	0.2294	0.2294	0.2294
Wheel Loader (6+ CY)	0.6107	0.5362	0.4686	0.4078	0.3538	0.3066	0.2661	0.2325	0.2057	0.1857	0.1725	0.1660	0.1660	0.1660	0.1660	0.1660
Track Loader (0-1.9 CY)	0.5268	0.4868	0.4496	0.4153	0.3839	0.3554	0.3297	0.3068	0.2868	0.2697	0.2555	0.2441	0.2355	0.2298	0.2270	0.2270
Track Loader (2+ CY)	0.6704	0.6147	0.5639	0.5180	0.4771	0.4412	0.4102	0.3841	0.3629	0.3467	0.3355	0.3292	0.3278	0.3278	0.3278	0.3278
Backhoe Loader (0-0.9 CY)	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
Backhoe Loader (1+ CY)	0.6195	0.5576	0.5007	0.4486	0.4016	0.3594	0.3222	0.2900	0.2626	0.2403	0.2228	0.2103	0.2028	0.2001	0.2001	0.2001
Integrated Toolcarrier (All Sizes)	0.7118	0.6304	0.5556	0.4874	0.4257	0.3706	0.3221	0.2802	0.2449	0.2162	0.1940	0.1784	0.1694	0.1670	0.1670	0.1670
Rigid-Frame Truck (0-99,999 lbs)	0.5511	0.5090	0.4696	0.4332	0.3996	0.3688	0.3410	0.3159	0.2938	0.2745	0.2580	0.2445	0.2337	0.2259	0.2209	0.2187
Rigid-Frame Truck (100,000+ lbs)	0.6053	0.5582	0.5134	0.4707	0.4302	0.3920	0.3559	0.3220	0.2903	0.2609	0.2336	0.2085	0.1857	0.1650	0.1465	0.1303
Articulated Truck (0-49,999 lbs)	0.5444	0.4783	0.4179	0.3633	0.3145	0.2715	0.2342	0.2028	0.1771	0.1572	0.1430	0.1347	0.1321	0.1321	0.1321	0.1321
Articulated Truck (50,000+ lbs)	0.5204	0.4550	0.3955	0.3421	0.2946	0.2531	0.2177	0.1882	0.1648	0.1473	0.1358	0.1304	0.1304	0.1304	0.1304	0.1304
Track Dozer (0-99 HP)	0.5537	0.5025	0.4554	0.4124	0.3734	0.3385	0.3077	0.2810	0.2584	0.2399	0.2254	0.2150	0.2087	0.2065	0.2065	0.2065
Track Dozer (100-199 HP)	0.6500	0.5783	0.5129	0.4536	0.4006	0.3537	0.3130	0.2786	0.2503	0.2283	0.2124	0.2027	0.1993	0.1993	0.1993	0.1993
Track Dozer (200-299 HP)	0.7084	0.6506	0.5978	0.5500	0.5071	0.4693	0.4364	0.4085	0.3856	0.3676	0.3547	0.3467	0.3437	0.3437	0.3437	0.3437
Track Dozer (300-399 HP)	0.6973	0.6230	0.5552	0.4940	0.4392	0.3911	0.3494	0.3144	0.2858	0.2638	0.2483	0.2394	0.2370	0.2370	0.2370	0.2370
Track Dozer (400+ HP)	0.5961	0.5253	0.4614	0.4043	0.3540	0.3105	0.2738	0.2440	0.2210	0.2048	0.1954	0.1928	0.1928	0.1928	0.1928	0.1928
Motor Grader (0-149 HP)	0.7229	0.6577	0.5976	0.5425	0.4924	0.4474	0.4074	0.3725	0.3426	0.3178	0.2980	0.2832	0.2735	0.2688	0.2688	0.2688
Motor Grader (150+ HP)	0.7408	0.6751	0.6146	0.5592	0.5090	0.4640	0.4241	0.3894	0.3599	0.3355	0.3163	0.3022	0.2933	0.2895	0.2895	0.2895
Wheel-Tractor Scraper (0-74,999 lbs)	0.8119	0.7322	0.6586	0.5910	0.5294	0.4739	0.4244	0.3809	0.3435	0.3122	0.2868	0.2675	0.2543	0.2471	0.2459	0.2459
Wheel-Tractor Scraper (75,000 lbs)	0.7102	0.6599	0.6119	0.5662	0.5229	0.4819	0.4432	0.4069	0.3729	0.3413	0.3120	0.2851	0.2605	0.2382	0.2183	0.2007

Salvage Value Reference: Lucko, G. *A Statistical Analysis and Model of the Residual Value of Different Types of Heavy Construction Equipment*. Diss. Virginia Polytechnic Institute and State University, 2003.

For light vehicles, Kelly Blue Book (KBB) values were used. Each vehicle in the 2008 data set was assumed to be in good condition and have the default options installed, and KBB's "private party" values were considered to be the best proxy for auction values. (Certainly it is realized that Kelly Bluebook is a consumer oriented publication and that in some cases, auction results may be the best data source for salvage values. In addition, the Blackbook and other value guides based on commercial auction data, such as Manhiem and Richie Brothers, may be more appropriate for DOT fleets for certain cases.) Once salvage values were determined for each of the light vehicles in the 2008 fleet, a variety of different models were examined to find the best fit for the data using the simplest model structure. A table of light vehicle classcodes is also provided below.

Table 6.5: Light Vehicle ClassCodes

20020	AUTOMOBILES, SEDAN, 100 THRU 112.9 IN. WHEELBASE
20030	AUTOMOBILES, SEDAN, 113 IN. WHEELBASE AND GREATER
25010	AUTOMOBILES, STATION WAGONS, UP TO 112.9 IN. WHEELBASE
400010	TRUCK, 4-WD UTILITY AND CARRYALL
400020	TRUCK, 4-WD PICKUP, ALL STYLES
400030	TRUCK, 2-WD UTILITY VEHICLE, 3961-5000 GVWR
410010	TRUCK, CARRYALL, UP TO 6950 LB GVWR
410020	TRUCK, CARRYALL, 7000 LB GVWR AND GREATER
420010	TRUCK, CARGO OR WINDOW VAN, MINI, UP TO 6200 LB GVWR
420020	TRUCK, CARGO OR WINDOW VAN, FULL-SIZE, 6200 LB GVWR & UP
430010	TRUCK, LIGHT DUTY, PICKUP, UP TO 4600 LB GVWR
430020	TRUCK, LIGHT DUTY, PICKUP, 4600 - 6199 LB GVWR
430030	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 4600-6199 GVWR
430040	TRUCK, HEAVY DUTY COMPACT, 4320-5600 GVWR
430050	TRUCK, EXTENDED CAB COMPACT, 4245-5034 GVWR
430070	TRUCK, EXTENDED CAB 1/2 TON, 6000-6799 GVWR
440010	TRUCK, LIGHT DUTY, PICKUP, 6200-7999 LB GVWR
440020	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 6200-7999 GVWR
440030	TRUCK, EXTENDED CAB 3/4 TON, 6800-9000 GVWR
450010	TRUCK, LIGHT DUTY, 8000-8599 GVWR, PICKUP BODY
450020	TRUCK, LIGHT DUTY, 8000-8599 GVWR, OTHER BODY STYLES
460010	TRUCK, LIGHT DUTY, 8600-14999 GVWR, PICKUP BODY
460020	TRUCK, LIGHT DUTY, 8600-14999 GVWR, OTHER BODY STYLES
470020	TRUCK, LIGHT DUTY, CR CAB, 7901-8599 GVWR, OTHER BODY STYLES
470030	TRUCK, LIGHT DUTY, CR CAB, 8600-14999 GVWR, OTHER BODY STYLES

Two final calibrated models are developed to estimate/forecast the equipment salvage value (at the end of each decision year) using its original purchase cost and the equipment age (represented in years) as the independent variables for both heavy and light vehicle types and they are provided respectively in the following:

- For Heavy Vehicle: $\text{Salvage Value} = \text{Original Purchase Price} * 0.6075 * e^{-0.078*Equipment\_Age}$
- For Light Vehicle: $\text{Salvage Value} = \text{Original Purchase Price} * e^{-0.14*Equipment\_Age}$

Also the R^2 values of both models (about 0.95) are fairly high, indicating that the models account for a high percentage of the total amount of variation in salvage values. Moreover, both types of vehicles have simplistic exponential model structures and the only inputs needed to determine the salvage value is the age of the vehicle (in years) and the original purchase cost, two data points that will undoubtedly be attached to the vehicle at all times. Most importantly, both exponential models can ensure that the salvage values will always be greater than 0 but will never exceed the original equipment purchase price for both heavy and light vehicles. After comprehensive testing, calibrating, and validating, both models seem to be very good and transferrable, and therefore are employed in the software to solving the ERO problem.

6.3.2 Purchase Cost Calculation

To derive the best models, several linear and nonlinear mathematical models were explored and advanced smoothing methods were developed to forecast equipment purchase cost (vs. model year), the annual O&M cost and the annual mileage (both vs. equipment age). The annual O&M cost per mile is also calculated using the equipment age as the only dependent variable.

In particular, the SAS macro source codes developed compare the following five different types of models: 1) Linear Model; 2) Polynomial Model; 3) Logarithm Model; 4) Exponential Model; and 5) Power Model. It should be noted that Types 2)-5) are all nonlinear models. The following shows the model forms:

1. Linear Model: $y = a + bx$;
2. Polynomial Model: $y = ax^3 + bx^2 + cx + d$;
3. Logarithm Model: $y = a \ln x + b$; By taking the regression of y vs. $\ln x$, one can get the model.
4. Exponential Model: $y = ae^{bx}$ or $\ln y = \ln a + bx$; By taking the regression of $\ln y$ vs. x, one can get the model.
5. Power Model: $y = ax^b$ or $\ln y = \ln a + b \ln x$; By taking the regression of $\ln y$ vs. $\ln x$, one can get the model.

The developed SAS macro codes have the capability of running through all linear and nonlinear models as described above. It can automate the model selection process by identifying the best model using the highest R-square value for forecasting the equipment purchase cost (using model year), and annual O&M cost/mile (using equipment age) for any chosen class code.In particular, it has been observed that for some classcodes even the best forecasting model with the highest R^2 value can produce negative forecasted purchase cost due to limited data or exhibited patterns within the data. In such cases the increasing adjusted purchase cost method is used for both code development and testing purposes. This method is currently under investigation and will be refined as the line of this research matures.

6.4 Summary

This chapter describes the TERM raw data cleaning and outlier treatments, as well as the cost forecasting and data processing performed by SAS macro codes. After the TERM data has been cleaned and analyzed, the SAS macro will generate several cost/mileage forecasting tables, which serve as the inputs to the DP-based optimization Engine to make the best possible keep/replace decision. Detailed information about the optimization engine will be discussed in the next chapter.

Chapter 7. DP-based Optimization Engine

7.1 Introduction

To solve the ERO problem, a DP-based optimization engine has been developed, which includes both DDP and SDP and uses both Bellman's and Wagner's approaches. The optimization engine receives the tables generated by SAS and uses the information to determine the optimized decision for both brand-new and used vehicles both with/without annual budget considerations.

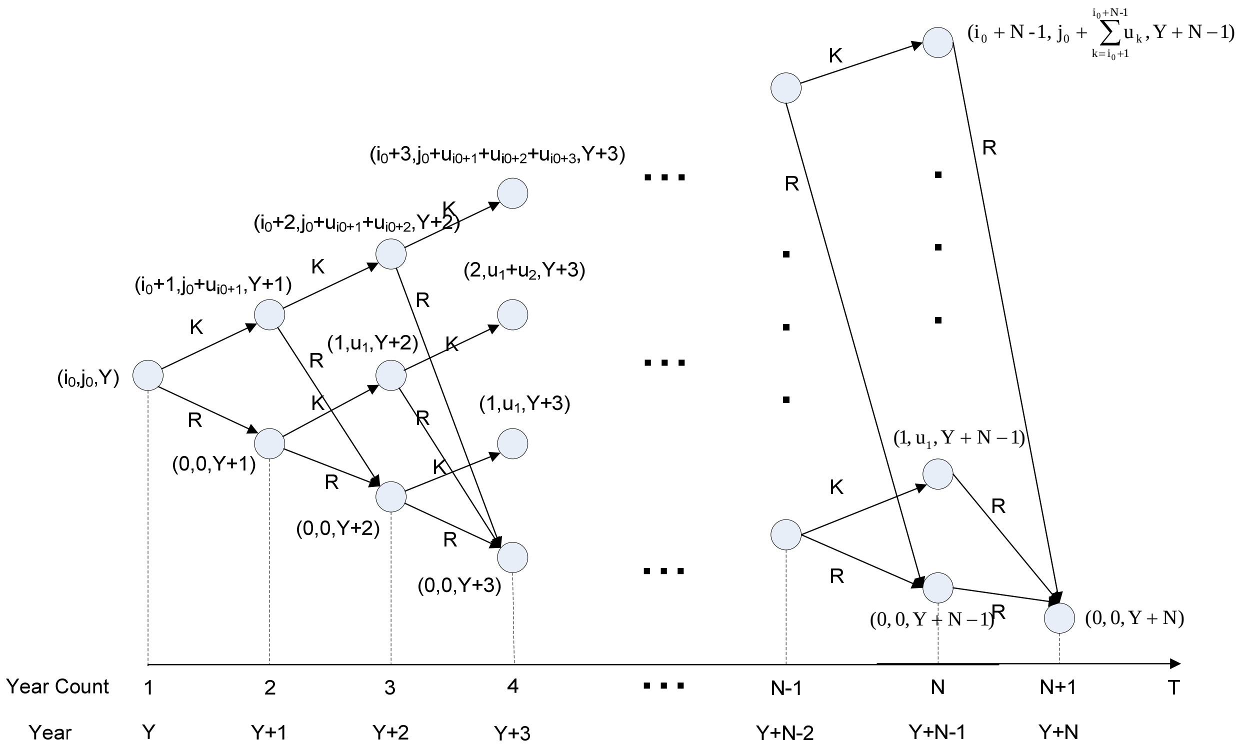
The following sections are organized as follows. Section 7.2 details the DDP solution approach, including the Bellman's and Wagner's Formulations. A small example is also designed and stepped-through to illustrate the Bellman's formulation and its solution process. Section 7.3 provides an explanation the SDP solution approach. The SDP state-space issue is also discussed along with the presentation of scenario reduction treatments to resolve such issue. Section 7.4 discusses the knapsack programming that is used in the second-round optimization to explicitly account for the ERO under annual budget constraint. Section 7.5 describes the computer implementation techniques developed to solve the ERO problem. Finally, section 7.6 concludes this chapter with a summary.

7.2 DDP Solution Approach

7.2.1 Bellman's DDP Formulation

Bellman (Bellman, 1995) introduced the first DDP solution to the finite horizon equipment replacement problem where the age of the asset defines the state of the system with the decision to keep or replace the asset at the end of each period (stage).

The Bellman DDP approach has been implemented so that the solution caters to TxDOT's needs in solving the ERO problem. The formulation is presented in the network shown in Figure 7.1. In this 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) the 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 0. An optimal policy with this model, in the form (K, K, R, K, K, …), gives the optimal decision at the beginning of each year. It can be seen that if an asset can be retained for a maximum of N 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($\frac{N(N+1)}{2} + 1$). Therefore, the computer complexity of Bellman's algorithm is O(N^2).



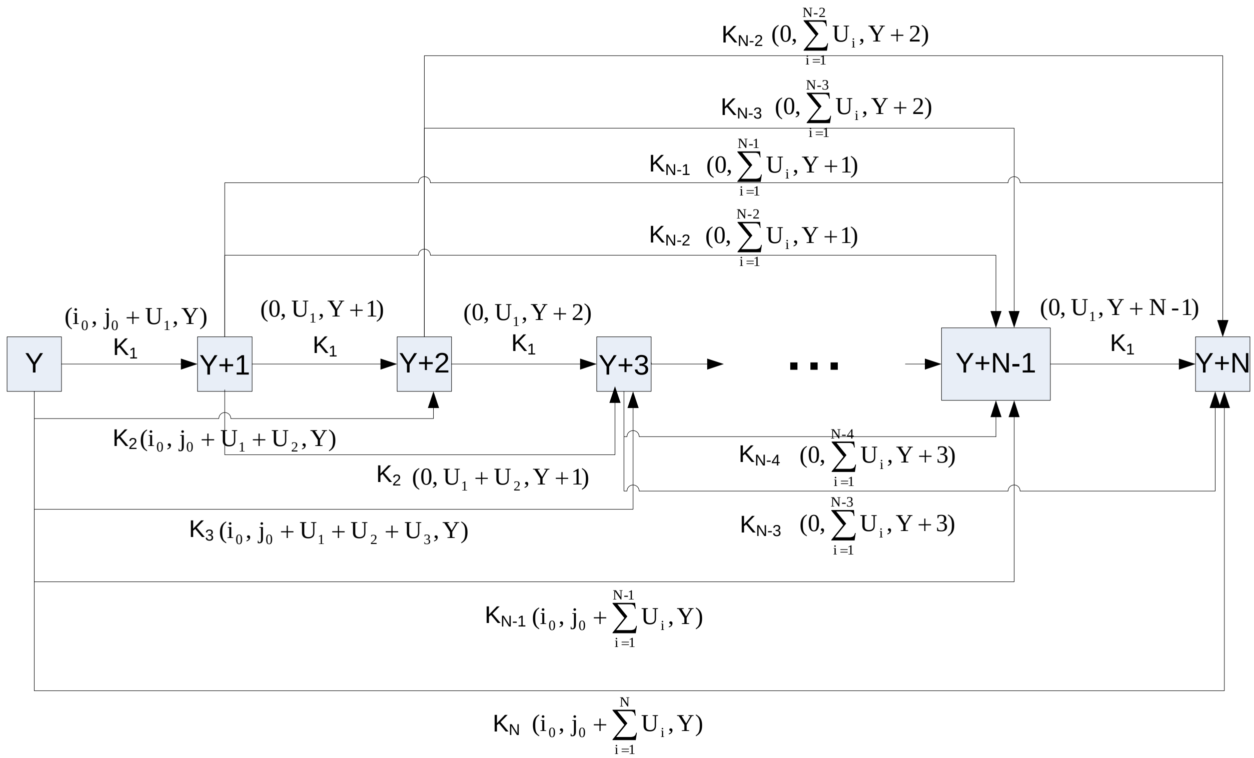
K – Keep asset
R – Replace asset
Note:
a. $(i_0 + N - 1, j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k, Y + N - 1)$ represents the status of a vehicle which is $(i_0 + N - 1)$-year old with its accumulative mileage being $(j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k)$ at the beginning of year $(Y + N - 1)$. u_k denotes 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 7.1: Bellman's DDP Approach to Solving the ERO Problem

7.2.2 Wagner's DDP Formulation

Wagner (Wagner, 1975) provided an alternative DP formulation to Bellman's solution in which the state of the system is the number of years an asset is to be kept. Let the value of N be again the maximum allowable service life for the asset. In Wagner's approach, the decisions are the number of periods, 1, 2, . . . , N to retain an asset rather than whether to keep or replace the asset as shown in Bellman's approach.

The Wagner DDP approach has been implemented to meet TxDOT's needs in solving the ERO problem. Figure 7.2 gives a network representation of Wagner's approach to the ERO problem. In this network, each node represents the time period and each arc represents the amount of time that the asset is retained. If an arc connects nodes t and $t+n$, then it represents retaining an asset for n periods. The arcs are shown as K_n, meaning that the asset is to be kept for n periods. Since there is a maximum of one state per period of time, N possible decisions for each state and N total periods, the problem can be solved in a computer complexity of $O(N^2)$ time, the same as Bellman's approach. Furthermore, in Wagner's formulation, an optimal policy can be represented in the form of (n_1, n_2, n_3,. . .) in which each value of n denotes the number of periods an asset is kept. It can be clearly seen that the policies derived from the Bellman and Wagner formulations are equivalent in that they can be converted to each other. For example, the time n_1 in the Wagner model is equivalent to n_1 consecutive decisions of K followed by one of R, etc.



Note:

a. State is the number of years an asset is to be kept as shown in the subscript of K. This tree describes how the decision is made for a piece of equipment that is i_0-year old with mileage j_0 starting at year Y through period year Y+N (i.e., N time period).

b. The trio $K_{N-4}\ (0, \sum_{i=1}^{N-4} U_i, Y+3)$ means the equipment is 0-year old with mileage 0 at the beginning of year Y+3 of the starting node. The mileage of u_i is the usage during each year at the end of which the equipment age becomes i-year old associated with the “Keep” decision and starting at year Y+3.

Figure 7.2: Wagner’s DDP Approach to Solving the ERO Problem

It should be noted that some pre-processing work is required with Wagner’s approach. The pre-computing allows for costs to be tracked so that all arcs can be solved and compared. In addition, both the Bellman and Wagner methods can be used to get identical optimal ERO solutions with almost the same efficiency (i.e., produce the same results in roughly the same amount of time). The Bellman approach may seem more straightforward; however, the Wagner method is better and easier to capture all necessary intricacies dealing with reality such as technological change and multiple challengers (Hartman and Rogers, 2006). For example, multiple challengers can be modeled by parallel arcs in the network connecting nodes between different time periods. Thus, preprocessing can eliminate inferior arcs before solving the problem. This is not possible with Bellman’s formulation as the state space must be expanded to include the challenger type. Also, by analyzing the state space growth for each of these extensions under various parameter assumptions, Hartman and Rogers (Hartman and Rogers, 2006) concluded that the Wagner method is more likely to succeed in solving large-scale problems (multiple challengers over long time horizons). For future solution development and testing, as well as algorithm comparison and benchmarking purposes, both approaches are chosen and illustrated here in this report.

7.2.3 Stepped-through Examples and Numerical Results

The following section presents a simple numerical example to illustrate and step-through the Bellman DDP solution process.

Suppose that a piece of equipment of a classocde 100010 is needed for four years (i.e., $N = 4$). At the beginning of the current decision year of 2004, one has 2-year-old equipment. The annual cost of operating and maintaining this equipment is a function of its age; and this cost function is given by: $C_1 = 10$, $C_2 = 20$, $C_3 = 40$, $C_4 = 50$, $C_5 = 60$, and $C_6 = 80$. The purchase price of a new unit of equipment is 60, i.e., $P_{2004} = 60$, $P_{2005} = 60$, $P_{2006} = 60$, and $P_{2007} = 60$. (This price can be easily changed and adapted to reflect price variations over time.) When such equipment is no longer needed at the end of year N, it will be salvaged and the salvage value is also a function of its age and the model year when it was bought. Since Y_0, the model year of a piece of equipment is already known and fixed in the calculation process, it is removed in the salvage value notation S_{iY_0} for the convenience of description and it is assumed that this function is given by: $S_1 = 30$, $S_2 = 25$, $S_3 = 20$, $S_4 = 15$, $S_5 = 10$, and $S_6 = 5$.

Figure 7.3 presents a Bellman DDP approach to solving this ERO problem for this simple example.

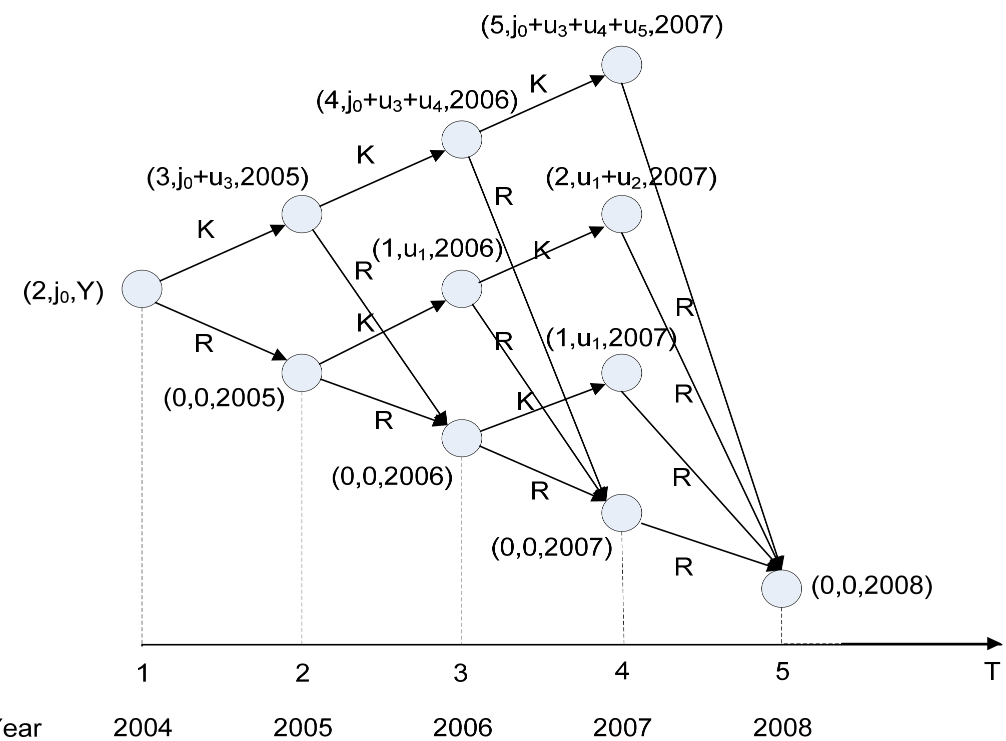


Figure 7.3: Bellman's DDP Approach to Solving a Simple Example of the ERO Problem

A "dynamic" replacement policy is a specification of a sequence of "keep" or "replace" actions, one for and at the beginning of each year. Two simple examples are the policy of replacing the equipment every year and the policy of keeping the equipment every year until salvaging it at the end of period *N*. The ERO for this simple case is to find the optimal policy which achieves the minimum total cost over the entire planning horizon.

To illustrate the calculation of total cost, consider the policy of replacing the equipment at the beginning of every year. Recall that the initial condition is to start with a 2-year-old equipment item. If this equipment is salvaged, then one will pay p for a new equipment unit, receive S_3 from the salvage at the end of the current year when the equipment turns 3-year-old, and incur C_3 for operating and maintaining the current equipment before replacing it with a new unit of equipment. It follows that the total cost for the first year is given by $P_{2004} - S_3 + C_3$. Similarly, for both the second and the third year, the annual cost is given by $P_{2005} - S_1 + C_1$ and $P_{2006} - S_1 + C_1$ respectively. Finally, since the equipment in service is salvaged, at age 6, at the end of year 4 (or at the beginning of year 5), the annual cost is given by $P_{2007} - S_1 + C_1$. Hence, the total cost over the entire planning horizon is:

$$\begin{aligned}
&(P_{2004} - S_3 + C_3) + (P_{2005} - S_1 + C_1) + (P_{2006} - S_1 + C_1) + (P_{2007} - S_1 + C_1)\\
&= (60 - 20 + 40) + (60 - 30 + 10) + (60 - 30 + 10) + (60 - 30 + 10)\\
&= 200.
\end{aligned}$$

As a second example, the total cost for the policy of never replacing the equipment until salvaging it at the end of the planning horizon can be easily calculated as:

$$\begin{aligned}
&(C_3) + (C_4) + (C_5) - (P_{2007} - S_6 + C_6)\\
&= 40 + 50 + 60 + (60 - 5 + 80)\\
&= 285.
\end{aligned}$$

It follows that this policy is worse than the previous one. Now, with two available actions for each year, the total number of possible policies is finite, and it is equal to $2^{N-1} = 2^3 = 8$. Therefore, continuation of similar calculations for the remaining 6 policies will eventually lead to the identification of the optimal policy. However, for problems with a longer planning horizon, a naïve approach (i.e., brutal enumeration) will be very time-consuming. As a result, an efficient and effective DDP approach is very desirable.

Beginning with the specification of the boundary condition, it is convenient to view the end of year 4 as the beginning of a final stage 5, where the only available action is to purchase a new unit of equipment, salvage the equipment in service, and operate and maintain this piece of equipment. Since the revenue received from salvaging a piece of equipment can be interpreted as a negative cost, this yields the boundary condition specified in the table below.

Stage 4:

i	$T_4^*(i)$
0	60+ (-30) + 10 = 40
1	60 + (-25) + 20 = 55
2	60 + (-20) + 40 = 80
5	60 + (-5) + 80 = 135

Note that the highest possible state is 5. This is a consequence of the fact that year 1 begins with a 2-year-old equipment and the planning horizon is 4 years. Also note that the state 3 and 4 are non-existing as can be seen from Figure 7.3.

Stage 3 is now considered, where the highest possible state is 4. For state 0, the one-stage costs associated with the keep and replace actions are $C_1 = 10$ and $P_{2006} - S_1 + C_1 = 60 - 30 + 10 = 40$, respectively. For state 1, the one-stage costs associated with the keep and replace actions are $C_2 = 20$ and $P_{2006} - S_2 + C_2 = 60 - 25 + 20 = 55$, respectively. Finally, for state 4, the one-stage costs associated with the keep and replace actions are $C_5 = 60$ and $P_{2006} - S_5 + C_5 = 60 - 10 + 60 = 110$, respectively. Substitution of these one-stage costs and the relevant $T_4^*(i)$'s from the stage-4 table above into the recursive computation relation

$$T_3^*(i) = \min [\, C_{i+1} + T_4^*(i+1),\ P_{2006} - S_{i+1} + C_{i+1} + T_4^*(0)] .$$

now yields the table below.

Stage 3:

	Actions			
i	Keep	Replace	$T_3^*(i)$	Optimal Action
0	10 + 55 = 65	60 + (-30) + 10 + 40 = 80	65	Keep
1	20 + 80 = 100	60 + (-25) + 20 + 40 = 95	95	Replace
4	60 + 135 = 195	60 + (-10) + 60 + 40 = 150	150	Replace

Next, move back one more stage to stage 2, where the highest possible state is 3. For all three states, the one-stage costs associated with the keep and replace actions are identical to the ones computed earlier in stage 3. Substitution of these one-stage costs and the relevant $T_3^*(i)$'s from the stage-3 table into the recursive computation relation

$$T_2^*(i) = \min [\, C_{i+1} + T_3^*(i+1),\ P_{2005} - S_{i+1} + C_{i+1} + T_3^*(0)] .$$

yields the table below.

Stage 2:

	Actions			
i	Keep	Replace	$T_2^*(i)$	Optimal Action
0	10 + 95 = 105	60 + (-30) + 10 + 65 = 105	105	Keep or Replace
3	50 + 150 = 200	60 + (-15) + 50 + 65 = 160	160	Replace

Note that for state 0, the costs associated with the keep and replace actions are tied at 105; therefore, both actions are optimal.

Finally, in stage 1, the only state is 2. Substitution of $C_3 = 40$, $P_{2004} - S_3 + C_3 = 60 - 20 + 40 = 80$, $T_2^*(0) = 105$, and $T_2^*(3) = 160$
into the recursive computation relation
$T_1^*(2) = min\, [\, C_3 + T_2^*(3),\ P_{2004} - S_3 + C_3 + T_2^*(0)]$.

yields the table below.

Stage 1:

	Actions			
i	Keep	Replace	$T_1^*(i)$	Optimal Action
2	40 + 160 = 200	60 + (-20) + 40 + 105 = 185	185	Replace

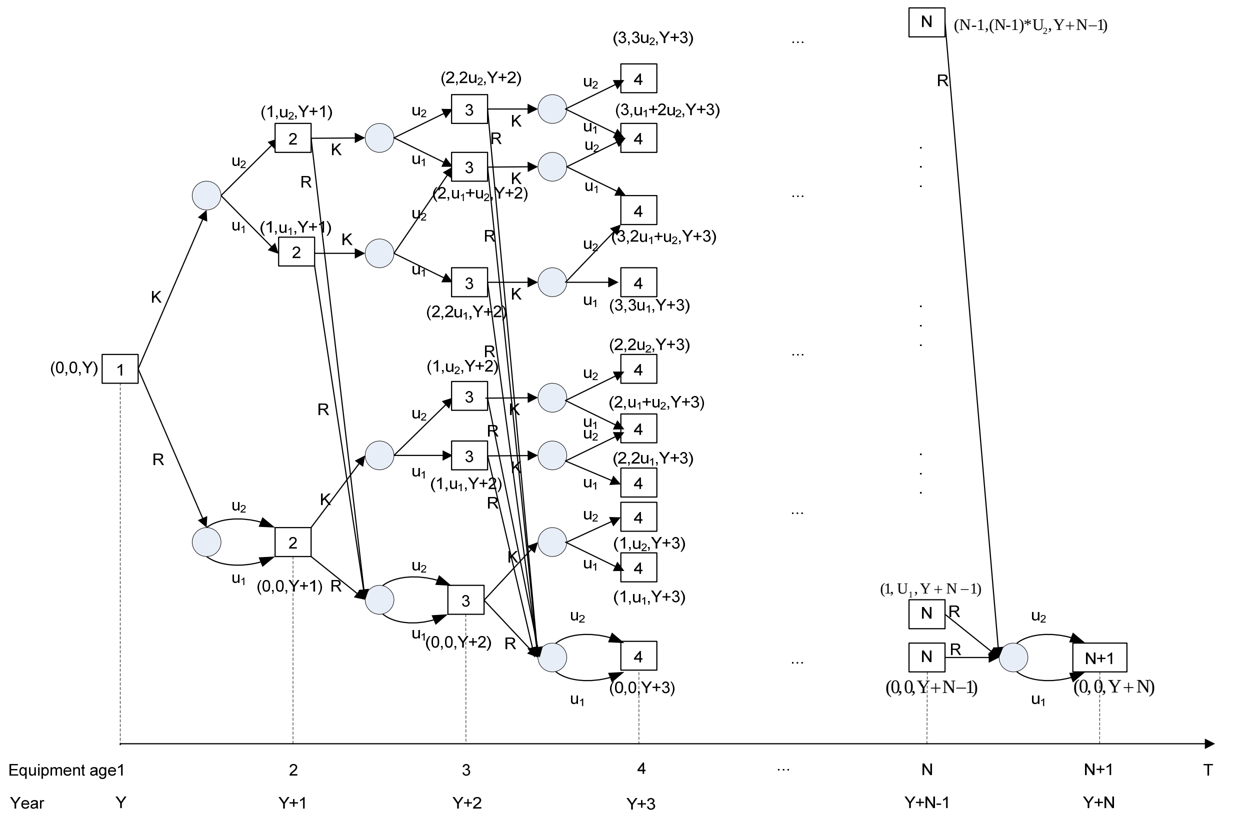
Since $T_1^*(2) = 185$, the minimal total cost from year 1 to the end of year 4, starting with a 2-year-old equipment in year 1, is 185.

The sequence of optimal actions can be read from the above tables sequentially as follows. An inspection of the stage-1 table shows that the original 2-year-old equipment unit should be immediately replaced. This implies that the state (age) of the equipment in service at the start of year 2 will be 0. Next, inspection of the first row of the stage-2 table shows that the equipment unit can either be kept or replaced in year 2. The first row of the stage-3 table shows that the new equipment unit should be kept at the start of year 3 if the decision is to replace the equipment at the start of year 2. Or it is shown that the now-1-year-old equipment should be replaced at the start of year 3 if the decision is to keep the equipment at the start of year 2. Finally, the unit of equipment should be replaced at the end of the planning horizon (i.e., the start of year 4). Thus, the optimal policy prescribes the following sequence of actions: “replace, replace, keep, and replace” or “replace, keep, replace, and replace”. This completes the solution of the simple example.

7.3 SDP Solution Approach

7.3.1 Bellman’s Formulation for the ERO SDP problem

Figure 7.3 shows a complete “Keep-Replace” Bellman’s formulation example starting with a brand-new equipment unit for the ERO SDP problem with uncertainty in vehicle utilization for the SDP 2-Level case after conducting the scenario reduction treatment. In Figure 7.3, 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 theses nodes defines the cumulative equipment utilization in the next stage. The path taken from the circular nodes are defined as u_1 and u_2 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 of the equipment unit after the final stage of the finite horizon problem. It should be also noted that the total cost would include the purchase cost, the expected annual O&M cost and salvage value.



K – Keep asset
R – Replace asset

Note:
a. (i, U_j, Y) represents the status of a vehicle which is i-year old with its accumulative mileage used being U_j 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.

Figure 7.4: A Complete "Keep-Replace" SDP Formulation for the ERO Problem with Uncertainty in Asset Utilization: the 2-Level Case after Conducting the Scenario Reduction Treatment

7.3.2 SDP State-Space Consideration and Scenario Reduction Treatments

As mentioned above, the Bellman's approach can be used to solve the ERO SDP problem. However, the use of DP is very limited in some cases - this phenomenon is commonly termed "curse of dimensionality". For example, the ERO SDP solution procedure without scenario reduction treatment has a general state-space issue that can result in the exponential growth in the computer memory and software computational time with the increase in time horizon. Two SDP approaches (SDP 2-Level and SDP 3-Level) have been developed based on the number of levels of annual equipment utilization each uses. The SDP 2-Level approach uses simple high and low utilization levels while the SDP 3-Level approach uses high, medium, and low utilization levels. For a simple case where the decision is to continuously keep until the maximum time window is reached, Figures 7.5.a and 7.5.b provide the SDP formulation for the ERO problem with uncertainty in asset utilization: "Curse of Dimensionality" for the naïve method for both the SDP 2-Level and the SDP 3-Level approaches and Table 7.1 provides a summary of the state-space for each approach with and without reduction treatment for the "Curse of Dimensionality" ERO Problem. As one can clearly see from Figures 7.5.a and 7.5.b and Table 7.1, both the total number of the asset utilization levels starting at next equipment age (i.e., nodes) grows exponentially as the equipment age increases even for a simple annual low or high mileage utilization case. In other words, if the SDP solution employs the Bellman's approach this simple way, the computer memory required and the software computational time will increase exponentially with the increase in time horizon. Specifically, it can be seen that both the number of arcs and the number of nodes for the SDP 2-Level and 3-Level naïve method scenarios grow at a rate of 2^N and 3^N respectively.

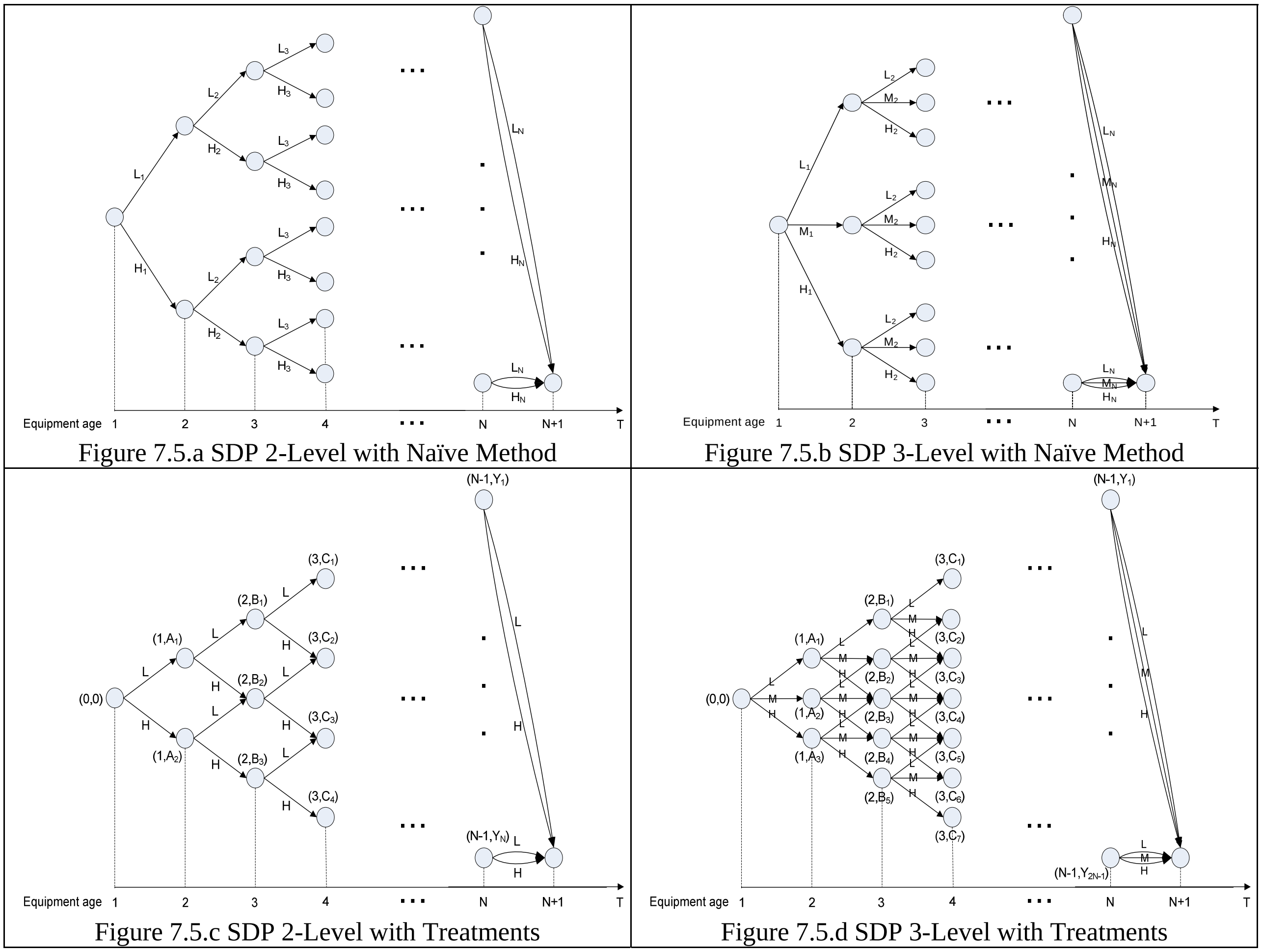


Figure 7.5.a SDP 2-Level with Naïve Method

Figure 7.5.b SDP 3-Level with Naïve Method

Figure 7.5.c SDP 2-Level with Treatments

Figure 7.5.d SDP 3-Level with Treatments

Figure 7.5: SDP 2-Level and SDP 3-Level Formulations for the ERO Problem with Uncertainty in Asset Utilization: "Curse of Dimensionality" for the Naïve Method, and Scenario Analysis and Reduction Treatments

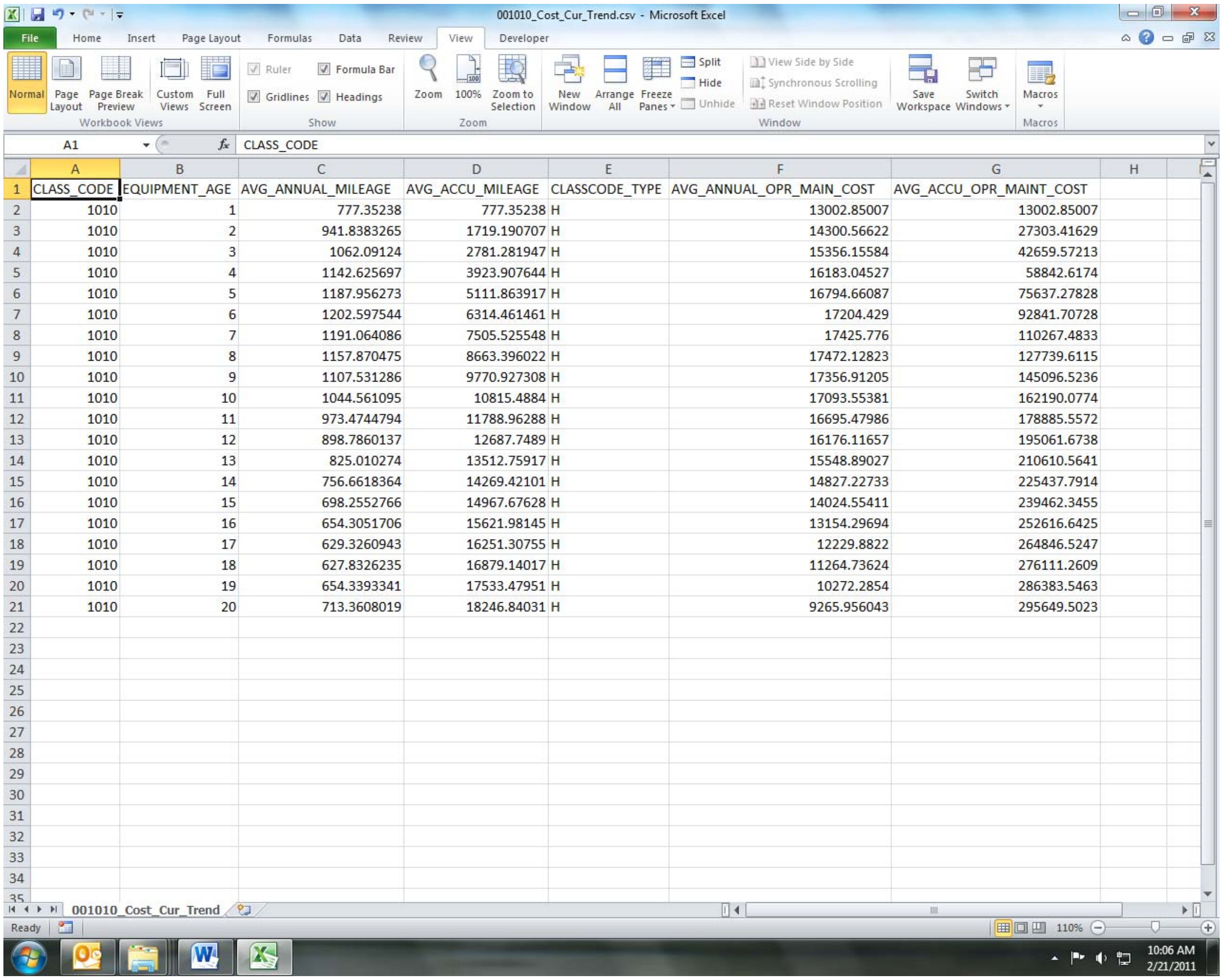
Clearly, implementing the Bellman's approach to solving the ERO SDP problem requires careful consideration and special treatments in order to resolve such issue as exponential growth in memory/performance as time horizon increases. Figures 7.5.c and 7.5.d provide the SDP formulation for the ERO problem with uncertainty in asset utilization: scenario analysis and reduction techniques for both the 2-Level and 3-Level cases. As one can clearly see from both Figures 7.5.c and 7.5.d, and Table 7.1 after the scenario reduction treatments, both the total number of asset utilization levels during the current equipment age (i.e., arcs) and the total number of the asset utilization levels starting at next equipment age (i.e., nodes) now grows linearly (rather than exponentially) as the equipment age increases. In other words, the computer memory and software computational time after the scenario reduction treatments will be significantly reduced compared to the naïve DP method and both will increase only linearly with the increase in time horizon.

Table 7.1: Summary of the State-Space for the SDP 2-Level and SDP 3-Level Formulations with and without Scenario Reduction Treatments

			Equipment Age						
		With Treatment?	1	2	3	4	…	N-1	N
Total Number of Asset Utilization Levels (Arcs) During the Current Equipment Age	SDP 2-Level	No	2	4	8	16	…	2^{N-1}	2^{N}
		Yes	2	4	6	8	…	2*(N-1)	2*N
	SDP 3-Level	No	3	9	27	81	…	3^{N-1}	3^{N}
		Yes	3	9	15	21	…	6*(N-1)-3	6*N-3
Total Number of the Asset Utilization Levels (Nodes) Starting at Next Equipment Age	SDP 2-Level	No	2	4	8	16	…	2^{N-1}	1
		Yes	2	3	4	5	…	N	1
	SDP 3-Level	No	3	9	27	81	…	3^{N-1}	1
		Yes	3	5	7	9	…	2*(N-1)+1	1

Additionally, once the SAS macro has finished the scenario reduction treatments, it generates the model year-based equipment purchase cost, the model year- and equipment age-based salvage value, and the equipment age-based annual operating and maintenance cost data with associated probabilities. This information is passed on to the Java codes and read to the SDP optimization engine to assist in the equipment optimization decisions. The SDP optimization framework is then used to solve the SDP-based ERO problem in the developed SDP optimization software. Certainly, the total cost would include the purchase cost; the expected annual O&M cost and salvage value.

Figure 6 provides a screen shot of the output of SAS macro and input to DDP optimization engine for the DDP-based ERO software. Figure 7 and 8 presents a screen shot of the output of SAS macro and input to SDP optimization engine for the SDP 2-Level and SDP 3-Level cases respectively after the scenario reduction treatments.



CLASS_CODE	EQUIPMENT_AGE	AVG_ANNUAL_MILEAGE	AVG_ACCU_MILEAGE	CLASSCODE_TYPE	AVG_ANNUAL_OPR_MAIN_COST	AVG_ACCU_OPR_MAINT_COST
1010	1	777.35238	777.35238	H	13002.85007	13002.85007
1010	2	941.8383265	1719.190707	H	14300.56622	27303.41629
1010	3	1062.09124	2781.281947	H	15356.15584	42659.57213
1010	4	1142.625697	3923.907644	H	16183.04527	58842.6174
1010	5	1187.956273	5111.863917	H	16794.66087	75637.27828
1010	6	1202.597544	6314.461461	H	17204.429	92841.70728
1010	7	1191.064086	7505.525548	H	17425.776	110267.4833
1010	8	1157.870475	8663.396022	H	17472.12823	127739.6115
1010	9	1107.531286	9770.927308	H	17356.91205	145096.5236
1010	10	1044.561095	10815.4884	H	17093.55381	162190.0774
1010	11	973.4744794	11788.96288	H	16695.47986	178885.5572
1010	12	898.7860137	12687.7489	H	16176.11657	195061.6738
1010	13	825.010274	13512.75917	H	15548.89027	210610.5641
1010	14	756.6618364	14269.42101	H	14827.22733	225437.7914
1010	15	698.2552766	14967.67628	H	14024.55411	239462.3455
1010	16	654.3051706	15621.98145	H	13154.29694	252616.6425
1010	17	629.3260943	16251.30755	H	12229.8822	264846.5247
1010	18	627.8326235	16879.14017	H	11264.73624	276111.2609
1010	19	654.3393341	17533.47951	H	10272.2854	286383.5463
1010	20	713.3608019	18246.84031	H	9265.956043	295649.5023

Figure 7.6: A Screen Shot of the Output of SAS Macro and Input to DDP Optimization Engine (DDP Case)

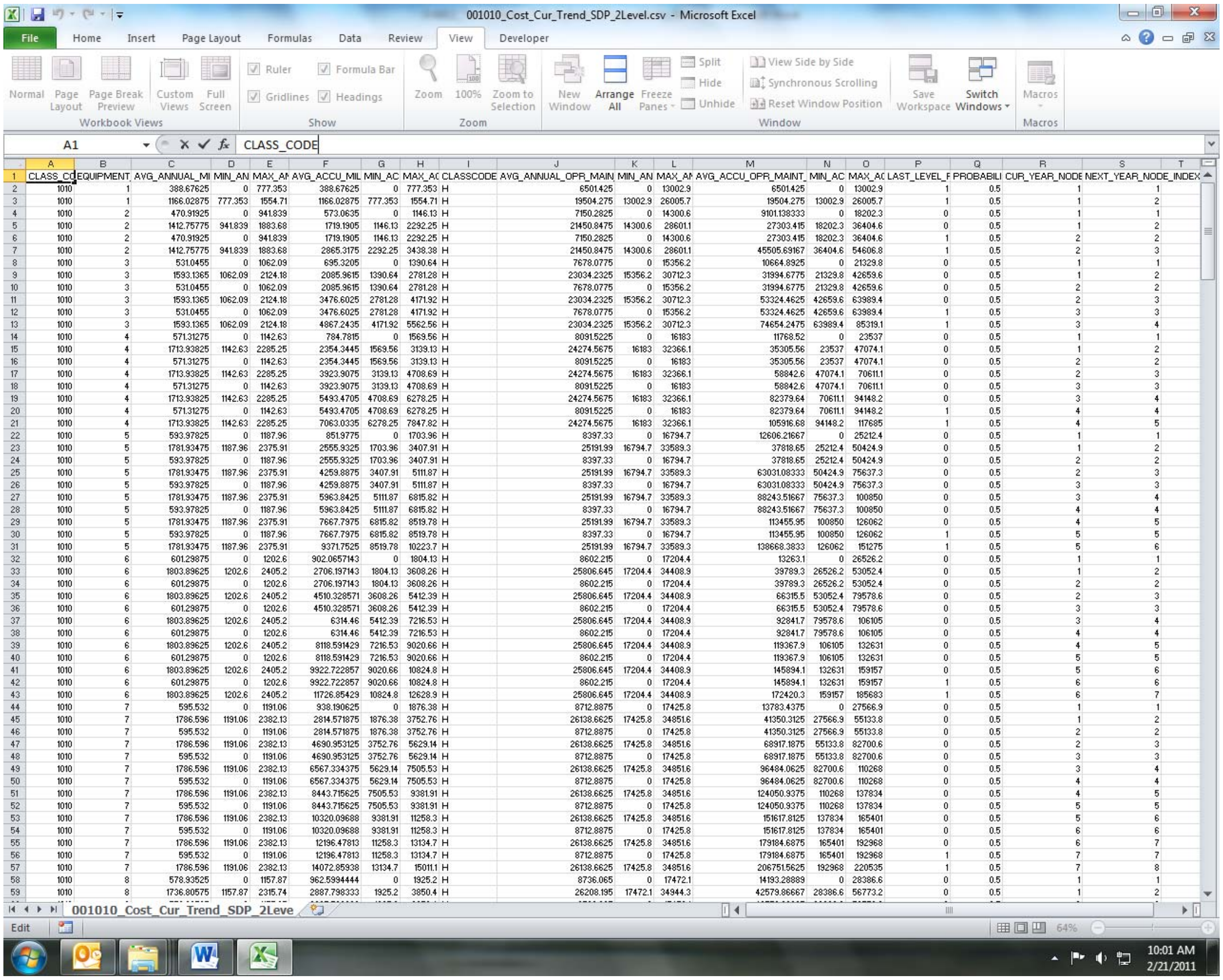
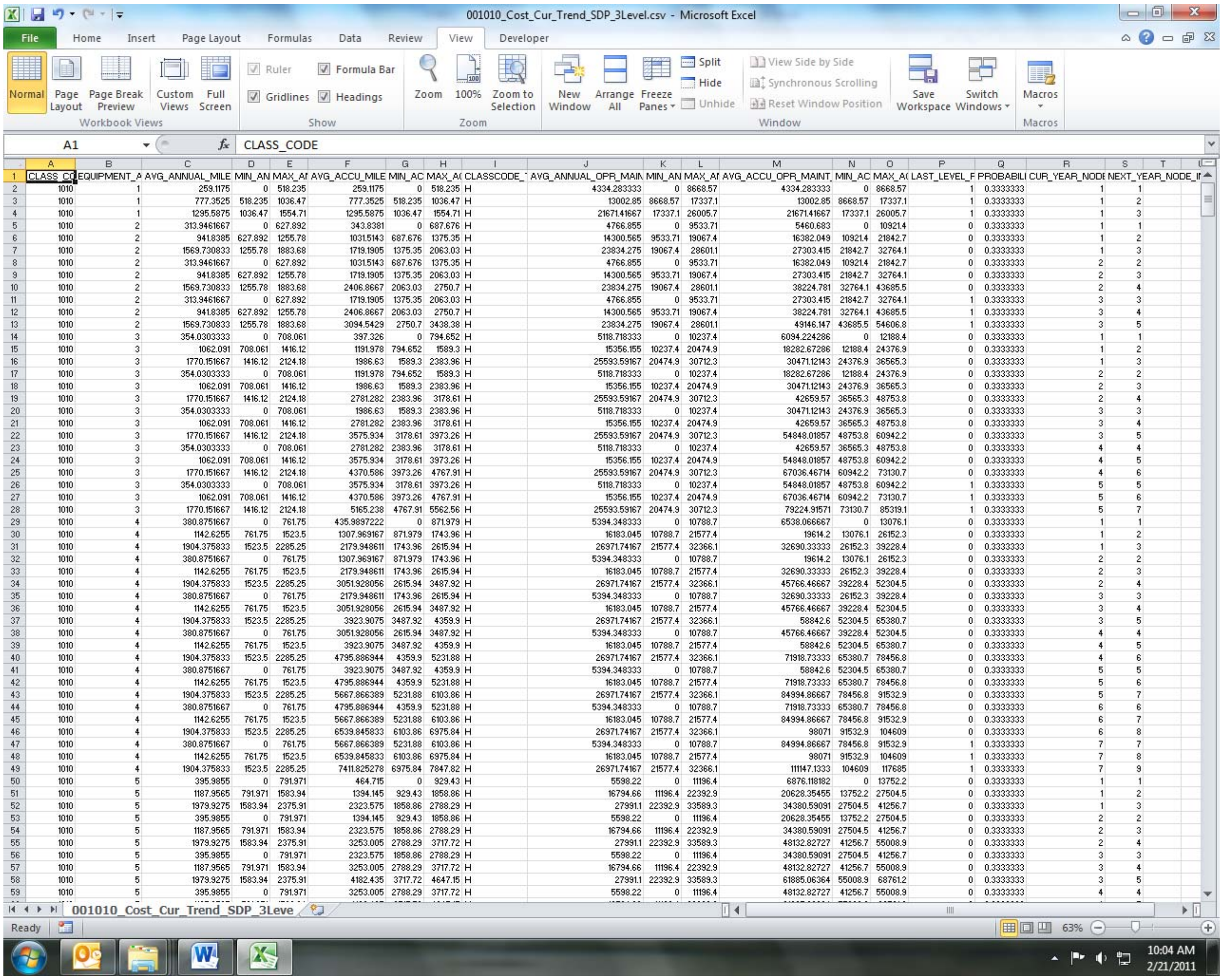


Figure 7.7: A Screen Shot of the Output of SAS Macro and Input to SDP Optimization Engine: the 2-Level Case After Using the Reduction Techniques (SDP 2-Level Case)



	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	CLASS_CO	EQUIPMENT_A	AVG_ANNUAL_MILE	MIN_AN	MAX_AI	AVG_ACCU_MILE	MIN_AC	MAX_A(	CLASSCODE_	AVG_ANNUAL_OPR_MAIN	MIN_AN	MAX_AI	AVG_ACCU_OPR_MAINT_	MIN_AC	MAX_A(	LAST_LEVEL_F	PROBABILI	CUR_YEAR_NODE	NEXT_YEAR_NODE_I
2	1010	1	259.1175	0	518.235	259.1175	0	518.235	H	4334.283333	0	8668.57	4334.283333	0	8668.57	1	0.3333333	1	1
3	1010	1	777.3525	518.235	1036.47	777.3525	518.235	1036.47	H	13002.85	8668.57	17337.1	13002.85	8668.57	17337.1	1	0.3333333	1	2
4	1010	1	1295.5875	1036.47	1554.71	1295.5875	1036.47	1554.71	H	21671.41667	17337.1	26005.7	21671.41667	17337.1	26005.7	1	0.3333333	1	3
5	1010	2	313.9461667	0	627.892	343.8381	0	687.676	H	4766.855	0	9533.71	5460.683	0	10921.4	0	0.3333333	1	1
6	1010	2	941.8385	627.892	1255.78	1031.5143	687.676	1375.35	H	14300.565	9533.71	19067.4	16382.049	10921.4	21842.7	0	0.3333333	1	2
7	1010	2	1569.730833	1255.78	1883.68	1719.1905	1375.35	2063.03	H	23834.275	19067.4	28601.1	27303.415	21842.7	32764.1	0	0.3333333	1	3
8	1010	2	313.9461667	0	627.892	1031.5143	687.676	1375.35	H	4766.855	0	9533.71	16382.049	10921.4	21842.7	0	0.3333333	2	2
9	1010	2	941.8385	627.892	1255.78	1719.1905	1375.35	2063.03	H	14300.565	9533.71	19067.4	27303.415	21842.7	32764.1	0	0.3333333	2	3
10	1010	2	1569.730833	1255.78	1883.68	2406.8667	2063.03	2750.7	H	23834.275	19067.4	28601.1	38224.781	32764.1	43685.5	0	0.3333333	2	4
11	1010	2	313.9461667	0	627.892	1719.1905	1375.35	2063.03	H	4766.855	0	9533.71	27303.415	21842.7	32764.1	1	0.3333333	3	3
12	1010	2	941.8385	627.892	1255.78	2406.8667	2063.03	2750.7	H	14300.565	9533.71	19067.4	38224.781	32764.1	43685.5	1	0.3333333	3	4
13	1010	2	1569.730833	1255.78	1883.68	3094.5429	2750.7	3438.38	H	23834.275	19067.4	28601.1	49146.147	43685.5	54606.8	1	0.3333333	3	5
14	1010	3	354.0303333	0	708.061	397.326	0	794.652	H	5118.718333	0	10237.4	6094.224286	0	12188.4	0	0.3333333	1	1
15	1010	3	1062.091	708.061	1416.12	1191.978	794.652	1589.3	H	15356.155	10237.4	20474.9	18282.67286	12188.4	24376.9	0	0.3333333	1	2
16	1010	3	1770.151667	1416.12	2124.18	1986.63	1589.3	2383.96	H	25593.59167	20474.9	30712.3	30471.12143	24376.9	36565.3	0	0.3333333	1	3
17	1010	3	354.0303333	0	708.061	1191.978	794.652	1589.3	H	5118.718333	0	10237.4	18282.67286	12188.4	24376.9	0	0.3333333	2	2
18	1010	3	1062.091	708.061	1416.12	1986.63	1589.3	2383.96	H	15356.155	10237.4	20474.9	30471.12143	24376.9	36565.3	0	0.3333333	2	3
19	1010	3	1770.151667	1416.12	2124.18	2781.282	2383.96	3178.61	H	25593.59167	20474.9	30712.3	42659.57	36565.3	48753.8	0	0.3333333	2	4
20	1010	3	354.0303333	0	708.061	1986.63	1589.3	2383.96	H	5118.718333	0	10237.4	30471.12143	24376.9	36565.3	0	0.3333333	3	3
21	1010	3	1062.091	708.061	1416.12	2781.282	2383.96	3178.61	H	15356.155	10237.4	20474.9	42659.57	36565.3	48753.8	0	0.3333333	3	4
22	1010	3	1770.151667	1416.12	2124.18	3575.934	3178.61	3973.26	H	25593.59167	20474.9	30712.3	54848.01857	48753.8	60942.2	0	0.3333333	3	5
23	1010	3	354.0303333	0	708.061	2781.282	2383.96	3178.61	H	5118.718333	0	10237.4	42659.57	36565.3	48753.8	0	0.3333333	4	4
24	1010	3	1062.091	708.061	1416.12	3575.934	3178.61	3973.26	H	15356.155	10237.4	20474.9	54848.01857	48753.8	60942.2	0	0.3333333	4	5
25	1010	3	1770.151667	1416.12	2124.18	4370.586	3973.26	4767.91	H	25593.59167	20474.9	30712.3	67036.46714	60942.2	73130.7	0	0.3333333	4	6
26	1010	3	354.0303333	0	708.061	3575.934	3178.61	3973.26	H	5118.718333	0	10237.4	54848.01857	48753.8	60942.2	1	0.3333333	5	5
27	1010	3	1062.091	708.061	1416.12	4370.586	3973.26	4767.91	H	15356.155	10237.4	20474.9	67036.46714	60942.2	73130.7	1	0.3333333	5	6
28	1010	3	1770.151667	1416.12	2124.18	5165.238	4767.91	5562.56	H	25593.59167	20474.9	30712.3	79224.91571	73130.7	85319.1	1	0.3333333	5	7
29	1010	4	380.8751667	0	761.75	435.9897222	0	871.979	H	5394.348333	0	10788.7	6538.066667	0	13076.1	0	0.3333333	1	1
30	1010	4	1142.6255	761.75	1523.5	1307.969167	871.979	1743.96	H	16183.045	10788.7	21577.4	19614.2	13076.1	26152.3	0	0.3333333	1	2
31	1010	4	1904.375833	1523.5	2285.25	2179.948611	1743.96	2615.94	H	26971.74167	21577.4	32366.1	32690.33333	26152.3	39228.4	0	0.3333333	1	3
32	1010	4	380.8751667	0	761.75	1307.969167	871.979	1743.96	H	5394.348333	0	10788.7	19614.2	13076.1	26152.3	0	0.3333333	2	2
33	1010	4	1142.6255	761.75	1523.5	2179.948611	1743.96	2615.94	H	16183.045	10788.7	21577.4	32690.33333	26152.3	39228.4	0	0.3333333	2	3
34	1010	4	1904.375833	1523.5	2285.25	3051.928056	2615.94	3487.92	H	26971.74167	21577.4	32366.1	45766.46667	39228.4	52304.5	0	0.3333333	2	4
35	1010	4	380.8751667	0	761.75	2179.948611	1743.96	2615.94	H	5394.348333	0	10788.7	32690.33333	26152.3	39228.4	0	0.3333333	3	3
36	1010	4	1142.6255	761.75	1523.5	3051.928056	2615.94	3487.92	H	16183.045	10788.7	21577.4	45766.46667	39228.4	52304.5	0	0.3333333	3	4
37	1010	4	1904.375833	1523.5	2285.25	3923.9075	3487.92	4359.9	H	26971.74167	21577.4	32366.1	58842.6	52304.5	65380.7	0	0.3333333	3	5
38	1010	4	380.8751667	0	761.75	3051.928056	2615.94	3487.92	H	5394.348333	0	10788.7	45766.46667	39228.4	52304.5	0	0.3333333	4	4
39	1010	4	1142.6255	761.75	1523.5	3923.9075	3487.92	4359.9	H	16183.045	10788.7	21577.4	58842.6	52304.5	65380.7	0	0.3333333	4	5
40	1010	4	1904.375833	1523.5	2285.25	4795.886944	4359.9	5231.88	H	26971.74167	21577.4	32366.1	71918.73333	65380.7	78456.8	0	0.3333333	4	6
41	1010	4	380.8751667	0	761.75	3923.9075	3487.92	4359.9	H	5394.348333	0	10788.7	58842.6	52304.5	65380.7	0	0.3333333	5	5
42	1010	4	1142.6255	761.75	1523.5	4795.886944	4359.9	5231.88	H	16183.045	10788.7	21577.4	71918.73333	65380.7	78456.8	0	0.3333333	5	6
43	1010	4	1904.375833	1523.5	2285.25	5667.866389	5231.88	6103.86	H	26971.74167	21577.4	32366.1	84994.86667	78456.8	91532.9	0	0.3333333	5	7
44	1010	4	380.8751667	0	761.75	4795.886944	4359.9	5231.88	H	5394.348333	0	10788.7	71918.73333	65380.7	78456.8	0	0.3333333	6	6
45	1010	4	1142.6255	761.75	1523.5	5667.866389	5231.88	6103.86	H	16183.045	10788.7	21577.4	84994.86667	78456.8	91532.9	0	0.3333333	6	7
46	1010	4	1904.375833	1523.5	2285.25	6539.845833	6103.86	6975.84	H	26971.74167	21577.4	32366.1	98071	91532.9	104609	0	0.3333333	6	8
47	1010	4	380.8751667	0	761.75	5667.866389	5231.88	6103.86	H	5394.348333	0	10788.7	84994.86667	78456.8	91532.9	1	0.3333333	7	7
48	1010	4	1142.6255	761.75	1523.5	6539.845833	6103.86	6975.84	H	16183.045	10788.7	21577.4	98071	91532.9	104609	1	0.3333333	7	8
49	1010	4	1904.375833	1523.5	2285.25	7411.825278	6975.84	7847.82	H	26971.74167	21577.4	32366.1	111147.1333	104609	117685	1	0.3333333	7	9
50	1010	5	395.9855	0	791.971	464.715	0	929.43	H	5598.22	0	11196.4	6876.118182	0	13752.2	0	0.3333333	1	1
51	1010	5	1187.9565	791.971	1583.94	1394.145	929.43	1858.86	H	16794.66	11196.4	22392.9	20628.35455	13752.2	27504.5	0	0.3333333	1	2
52	1010	5	1979.9275	1583.94	2375.91	2323.575	1858.86	2788.29	H	27991.1	22392.9	33589.3	34380.59091	27504.5	41256.7	0	0.3333333	1	3
53	1010	5	395.9855	0	791.971	1394.145	929.43	1858.86	H	5598.22	0	11196.4	20628.35455	13752.2	27504.5	0	0.3333333	2	2
54	1010	5	1187.9565	791.971	1583.94	2323.575	1858.86	2788.29	H	16794.66	11196.4	22392.9	34380.59091	27504.5	41256.7	0	0.3333333	2	3
55	1010	5	1979.9275	1583.94	2375.91	3253.005	2788.29	3717.72	H	27991.1	22392.9	33589.3	48132.82727	41256.7	55008.9	0	0.3333333	2	4
56	1010	5	395.9855	0	791.971	2323.575	1858.86	2788.29	H	5598.22	0	11196.4	34380.59091	27504.5	41256.7	0	0.3333333	3	3
57	1010	5	1187.9565	791.971	1583.94	3253.005	2788.29	3717.72	H	16794.66	11196.4	22392.9	48132.82727	41256.7	55008.9	0	0.3333333	3	4
58	1010	5	1979.9275	1583.94	2375.91	4182.435	3717.72	4647.15	H	27991.1	22392.9	33589.3	61885.06364	55008.9	68761.2	0	0.3333333	3	5
59	1010	5	395.9855	0	791.971	3253.005	2788.29	3717.72	H	5598.22	0	11196.4	48132.82727	41256.7	55008.9	0	0.3333333	4	4

Figure 7.8: A Screen Shot of the Output of SAS Macro and Input to SDP Optimization Engine: the 3-Level Case After the Reduction Techniques (SDP 3-Level Case)

7.4 Knapsack Programming

As mentioned before, the proposed DP solution algorithms have been implemented via backward recursion and a DP-based solution software has been developed to minimize the total costs in this report. The software developed can recommend an optimized solution on whether to retain or replace a unit of equipment for both brand-new and used vehicles both with and without annual budget considerations. This decision is based on the equipment class, age, mileage, salvage value, and replacement cost which come from SAS macro codes. The knapsack programming optimization method is used to solve the ERO problem with budget consideration in order to account for the optimal replacement of multiple candidate equipment units subject to the annual budget constraint.

The knapsack problem is a problem in combinatorial optimization: Given a set of items, each with a weight and a value, determine the number of each item to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible. It derives its name from the problem faced by someone who is constrained by a fixed-size knapsack and must fill it with the most useful items (Hillier and Lieberman, 2005). In the

ERO context, the size of the knapsack is determined by the annual budget and the set of items is the list of candidate equipment units for replacement. The cost of replacement is modeled as the weight of the items and value of the items is represented as the cost savings of each replacement compared to the benchmark solution. The program maximizes the benefit of replacement compared to the benchmark decision and chooses the most optimal solution (i.e., an optimal list of equipment units for replacement) that fits the annual budget for the decision year.

In summary, if the software user needs to make ERO decisions only at the classcode level (i.e. for brand-new equipment units), without budget consideration, then only the DP optimization will be called upon to determine optimal solution (i.e. how many years to keep and when to replace for the entire solution window) as a general guideline. However, if the software user needs to make ERO decisions for each individual or all the equipment units, then both the DP and Knapsack programming optimizations will be executed to determine the optimal solution list of candidate equipment units for replacement for the current decision year subject to the specified annual budget constraint. In the latter case, the cost increase associate with immediate or delayed replacement decisions compared to the DP-based optimized solutions will be used as the input to the knapsack programming optimization. The knapsack programming optimization will seek to maximize the benefits for the user given the specified annual budget for the decision year and produces a final equipment replacement recommendation file which contains the optimal equipment replacement results. Detailed information can be found in Appendix A to this report.

7.5 Computer Implementation Techniques

To successfully implement the Bellman and Wagner formulations to solve the ERO problem, an efficient and effective data structure is designed and implemented by developed Java computer codes. The model year-based equipment purchase cost, the equipment age-based salvage value, and the equipment age-based annual operating and maintenance cost data that come from SAS (Fan et al, 2011a) are read and processed by the Java codes through three steps/layers within the Optimization Engine. The first layer is reading the classcode; the second layer is reading the equipment age and the third layer is reading the equipment utilization and associated probability calculated based on the TxDOT's historical equipment utilization data over all available years (to accommodate the different mileage usage levels). A series of dynamically allocated arrays are developed to store the data (Fan et al, 2011b; 2011c). Both Bellman's and Wagner's approaches are solved backward and the recursive functions are called efficiently. Most importantly, the way that the DP-based Bellman and Wagner formulations are handled, work effectively and efficiently for both DDP- and SDP-based ERO solutions. Put another way, different utilization levels can be accommodated by the current data structures very efficiently.

7.6 Summary

As one of the most critical components to solve the ERO problem, the DP-based optimization engine, which makes the best keep/replace decisions, is discussed in detail in this chapter. Both the DDP and SDP solution approaches, and both Bellman's and Wagner's formulations, as well as the knapsack programming optimization, are described in detail along with the computer implementation techniques used to develop this software. These solution approaches have been implemented and DP-based ERO software has been developed successfully. In next chapter, detailed case studies and comprehensive numerical results will be presented.

Chapter 8. Case Studies and Numerical Results

8.1 Introduction

In chapter 7, a DP-based optimization engine, which consists of the DDP and SDP based solution approaches, both Bellman's and Wagner's formulations, as well as the Knapsack programming in the second round optimization (which can account for the ERO with budget consideration), have been discussed, implemented and developed for solving the ERO problem. A series of unit tests and comprehensive logic tests were designed and conducted to ensure the correct logic of all three major components, the Java GUI, the DP-based Optimization Engine, and SAS macro codes. Comprehensive integration tests were also performed for software integration purposes among all components and this effort has been successful as well. Many EXCEL spreadsheets were also developed to test and benchmark the optimization engine solution by checking all of the computed costs at each stage and confirming other calculated values. Finally, this DP-based ERO software system has also been validated and tested using current TxDOT TERM data for many classcodes. The results are very promising and also very encouraging as indicated by the fact that substantial cost savings compared to the current TxDOT experience/rule-based replacement criteria can be estimated.

The rest of this chapter is organized as follows. Section 8.2 provides the statistical analyses numerical results obtained as results of the SAS macro codes. Section 8.3 describes the representative DDP-based optimization results using two classcodes (one heavy vehicle and one light vehicle) from the real world TERM data as examples. Section 8.4 discusses the SDP-based optimization results using the same two classcodes as examples. Finally, section 8.5 concludes this chapter with a summary.

8.2 Statistical Analyses Numerical Results

As mentioned in sections 6.2 and 6.3, after a series of data reading, cleaning, processing, and outlier treatments steps are undertaken by SAS macro code, a clean dataset without data errors and outliers is obtained. Based on this dataset, in-depth statistical modeling and numerical result analyses are performed. Although one might argue that the statistical modeling and numerical analyses may most likely depend upon the specific classcode chosen, it has been confirmed after comprehensive testing that all numerical results of all classcodes seem to follow similar patterns and exhibit shared general characteristics. The subsequent section uses classcode 540020 as an example to present the underlying characteristics and trends that are very representative of most classcodes in the real world of TxDOT's TERM data.

8.2.1 Purchase Cost vs. Model Year

Figures 8.1 through 8.14 provide graphs presenting the relationships of purchase cost vs. model year, and O&M cost/mile/down time vs. equipment age for vehicle class code 540020. As one can clearly see from the first four graphs, as model year increases, the non-adjusted original total purchase cost increases noticeably. However, if one takes into account the inflation rate, the adjusted total purchase cost seems to decrease initially and then increase slightly into the future although the pattern is not very clear. This is probably because the equipment normally gets more expensive as the technology usually advances and therefore, the purchase cost in the absolute dollar values increases along the years. However, accounting for economy-dependent inflation rate adds more complexities and therefore will make the prediction for the inflation-adjusted total purchase cost less reliable and unpredictable. In this regard, the results might suggest that it would be better for one to forecast the original purchase price first and then make the inflation adjustment rather than forecasting the adjusted total purchase cost directly.

8.2.2 O&M Cost/Mileage/Down Time vs. Equipment Age

Graphs 8.5 through 8.14 show several very interesting results. For example, as equipment age increases, the total O&M cost per mile (or total O&M cost per hour) increases. This is probably true because new equipment generally becomes more fuel-efficient over the years as the technology advances. Another important point is that as equipment ages, both the equipment utilization (i.e., actual usage in miles or hours) and commit hours decrease noticeably. In particular, the adjusted total O&M cost increases initially and then decreases as equipment ages. The down time also exhibits the same pattern, i.e., it increases initially and then decreases as equipment ages. Again, both phenomena might be due to the fact that as equipment gets older, it becomes relatively less efficient and the risk of equipment being down generally increases. As a result, the adjusted total O&M cost increases initially and the down time might also increase (particularly when equipment utilization is equal or close-to equal). On the other hand, as equipment ages, the equipment utilization decreases. These two effects will cancel each other up to a point, and after that point, the decreases in the O&M cost due to less utilization will outweigh and therefore the adjusted total O&M cost will begin to decrease. The same logic applies to the down time. The decreases in equipment utilization forces the down time to begin to decrease after a certain point.

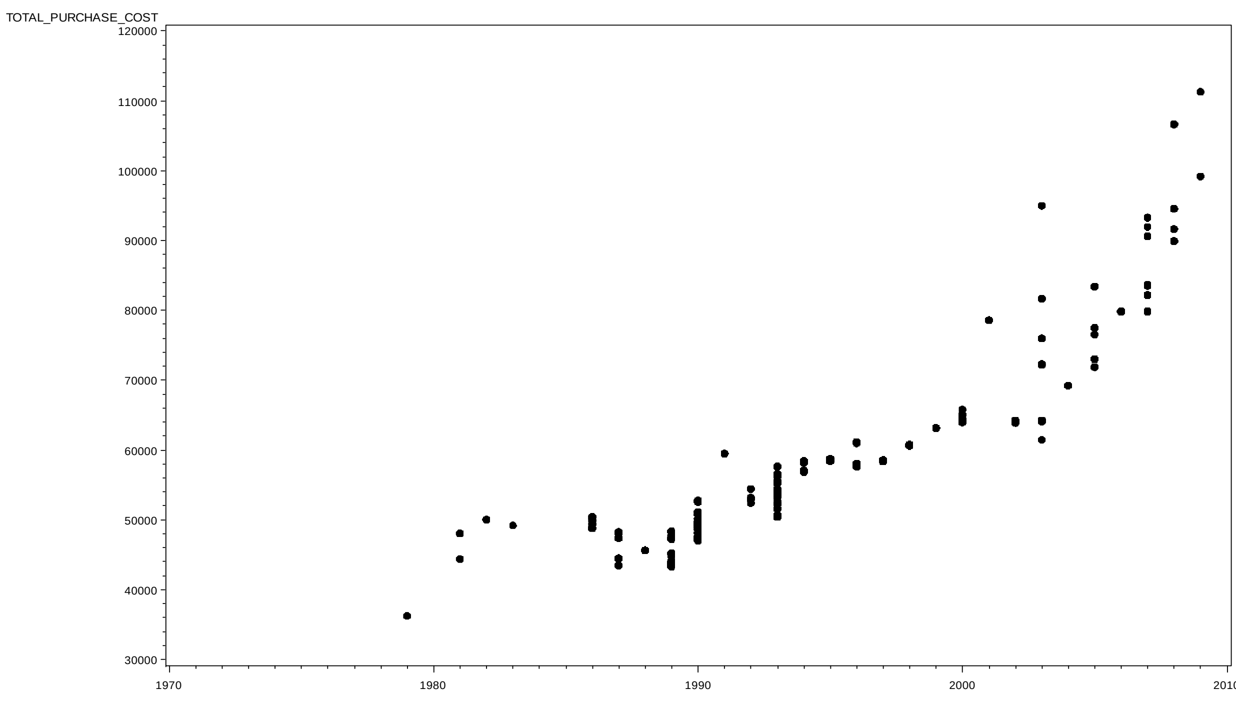


Figure 8.1: Non-adjusted Original Total Purchase Cost vs. Model Year

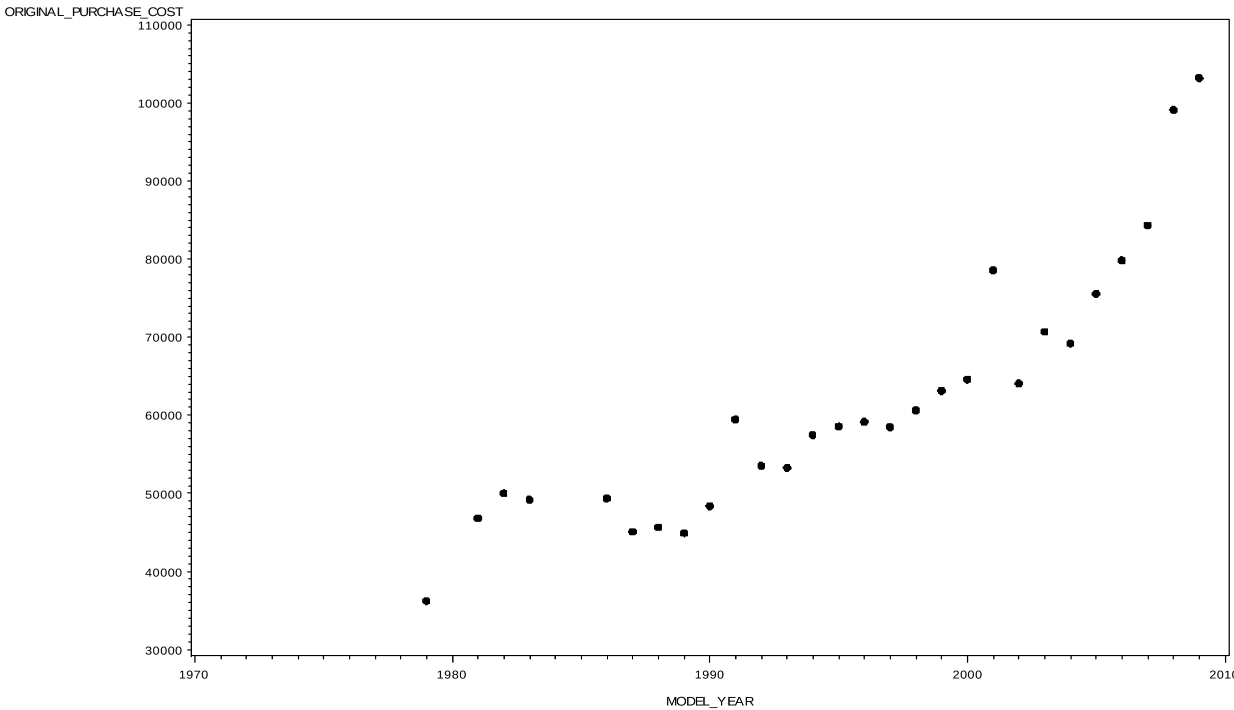


Figure 8.2: Average Non-adjusted Original Total Purchase Cost vs. Model Year

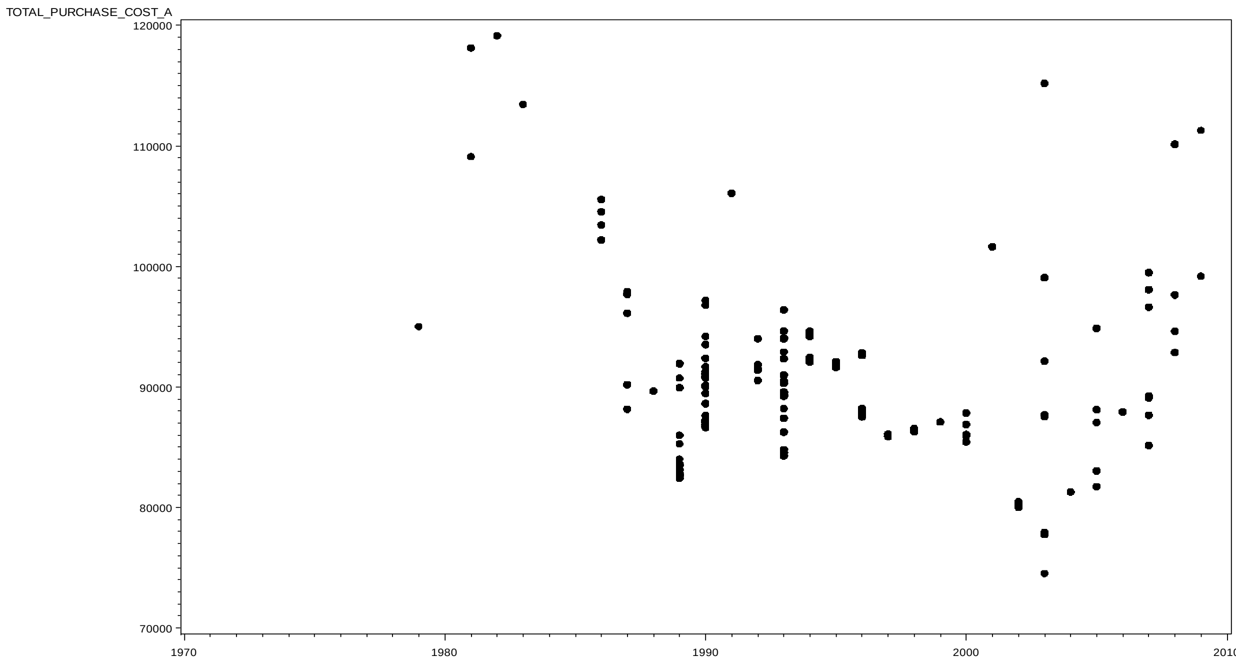


Figure 8.3: Inflation-adjusted Total Purchase Cost vs. Model Year

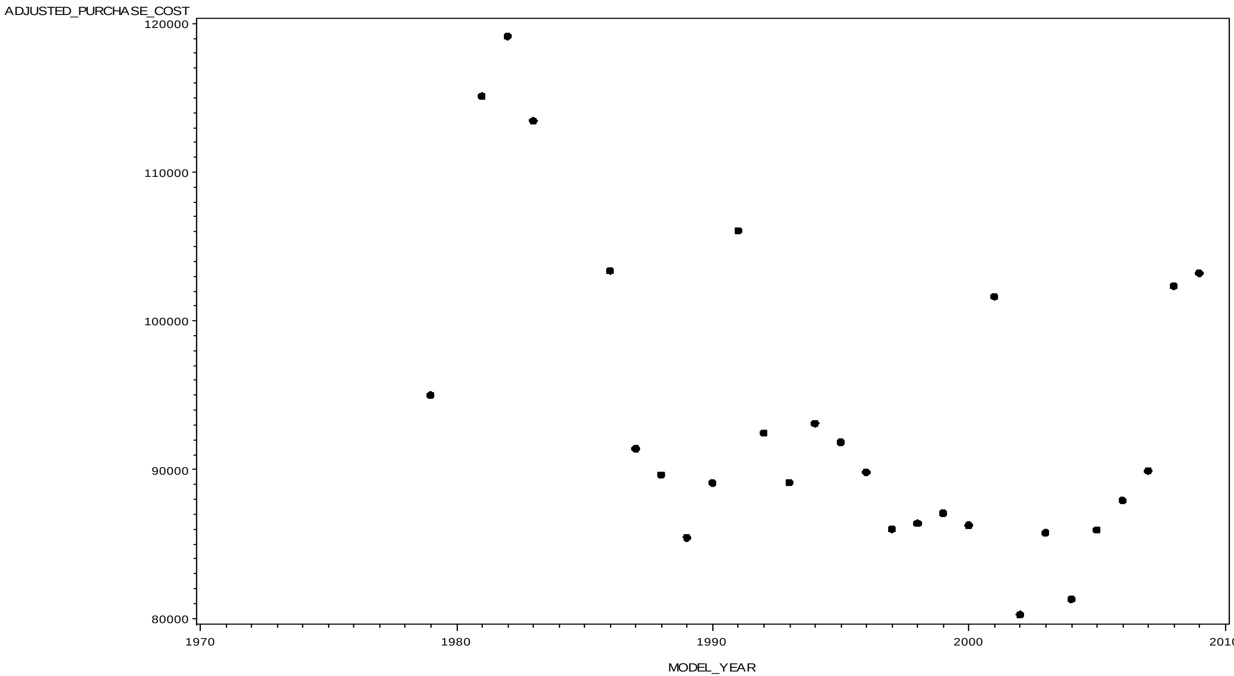


Figure 8.4: Average Adjusted Total Purchase Cost vs. Model Year

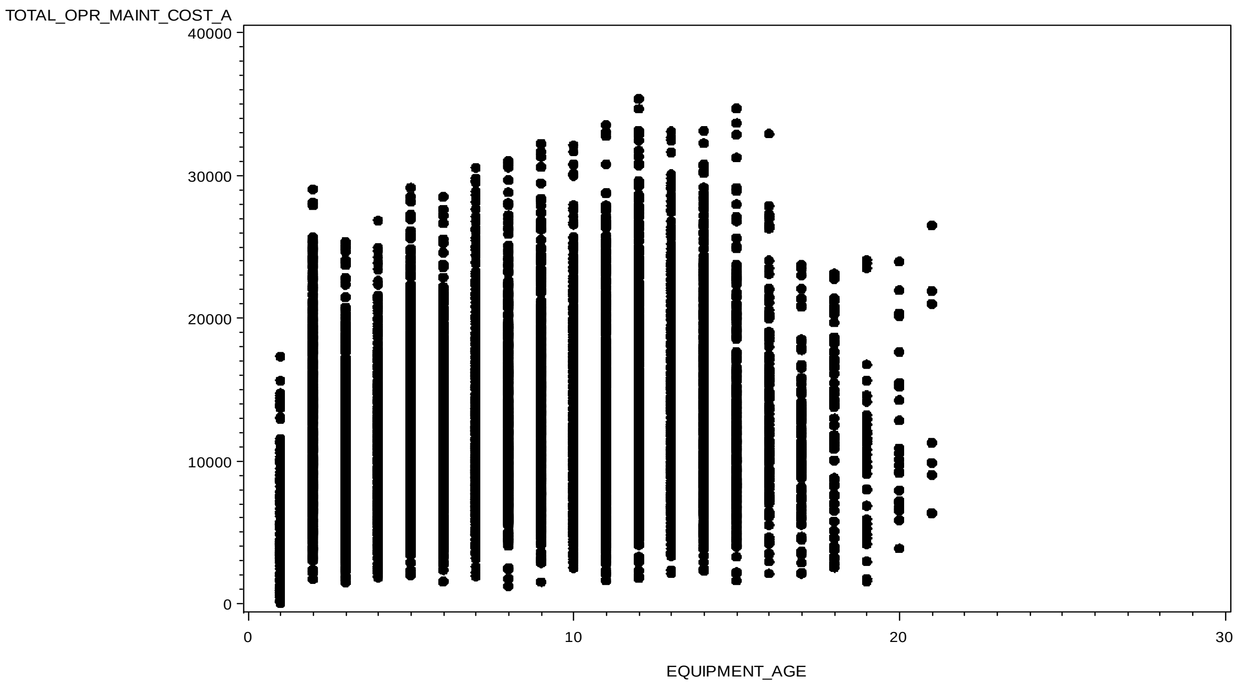


Figure 8.5: Inflation-adjusted Total O&M Cost vs. Equipment Age

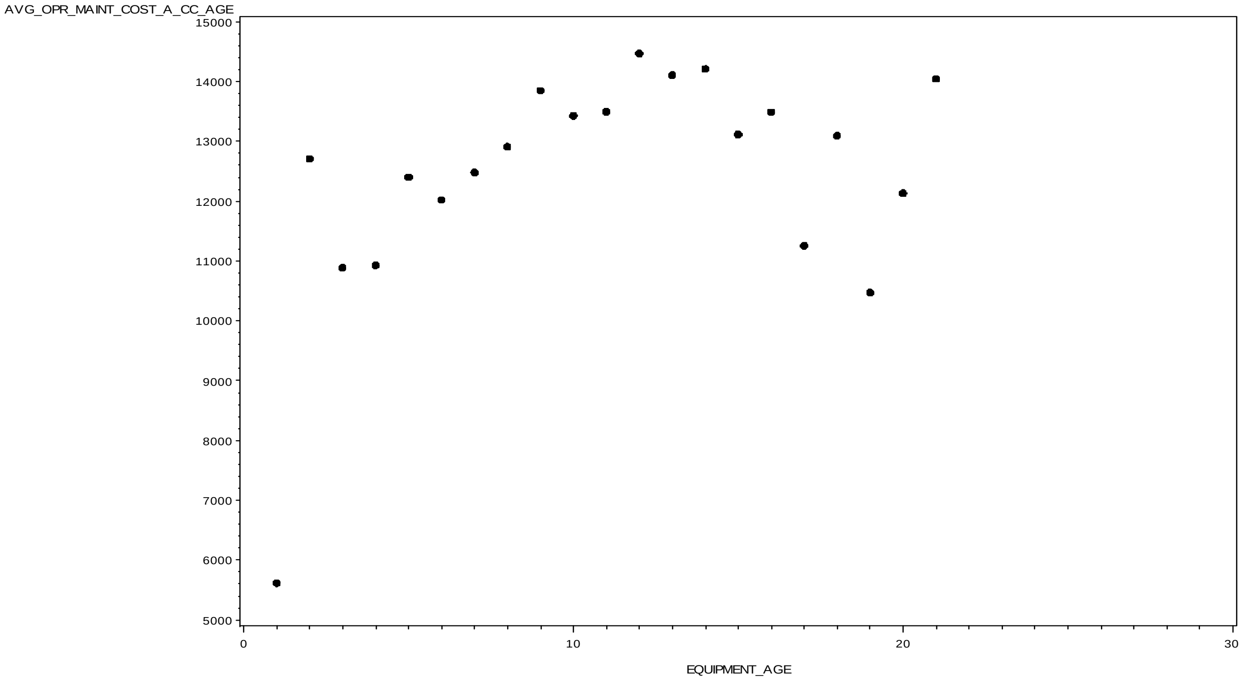


Figure 8.6: Average Adjusted Total O&M Cost vs. Equipment Age

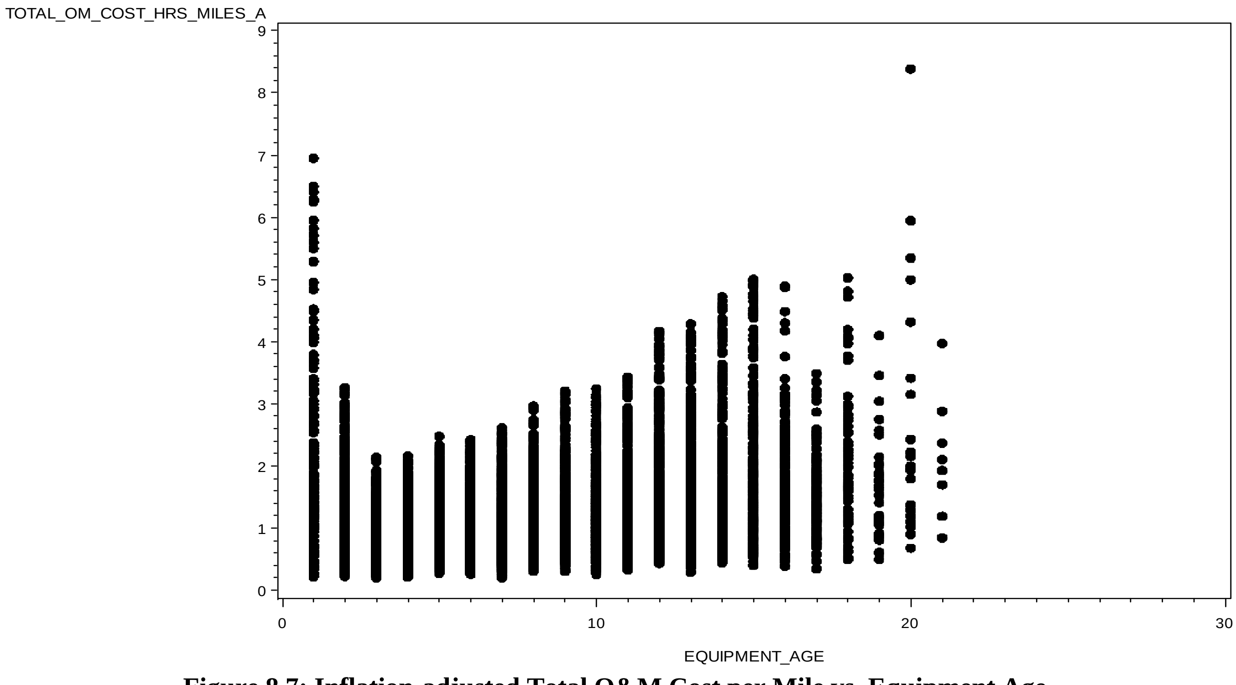


Figure 8.7: Inflation-adjusted Total O&M Cost per Mile vs. Equipment Age

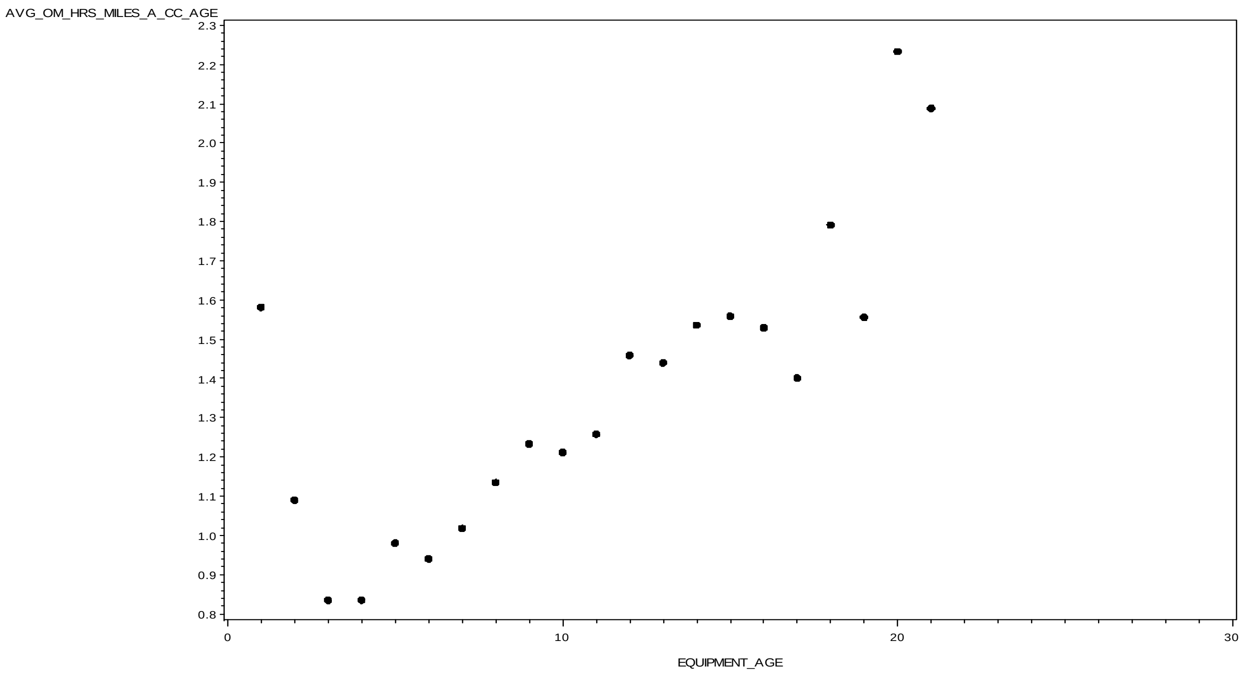


Figure 8.8: Average Adjusted Total O&M Cost per Mile vs. Equipment Age

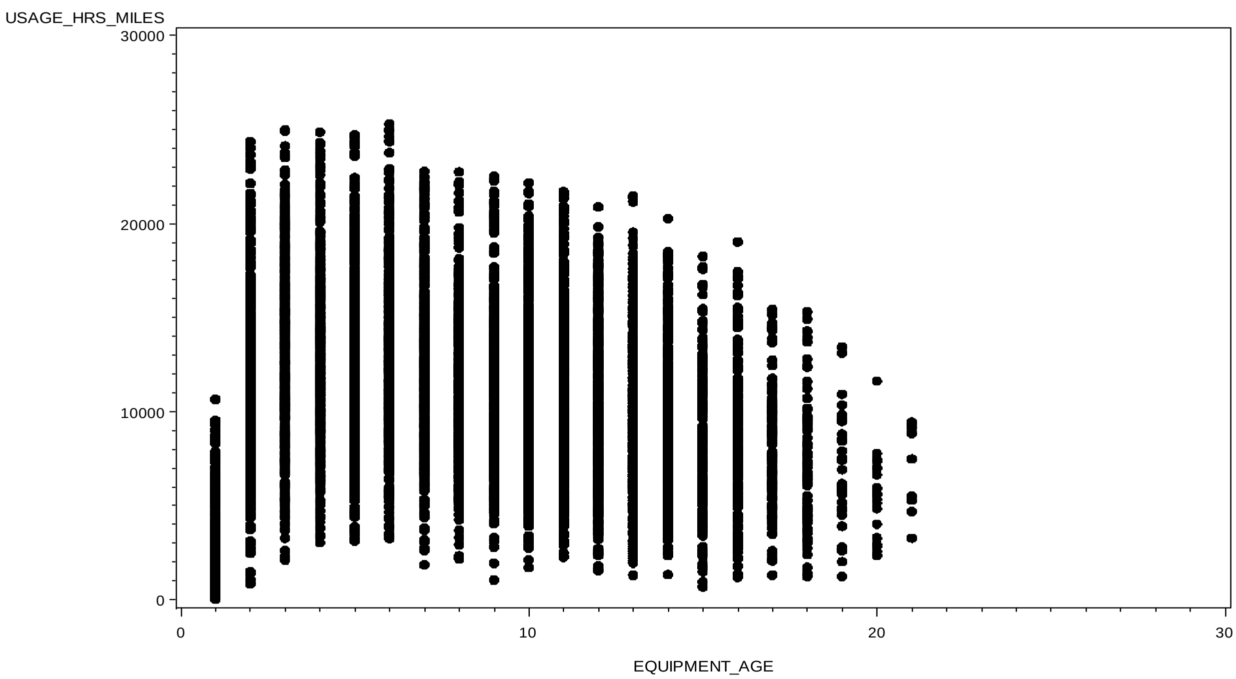


Figure 8.9: Usage Miles vs. Equipment Age

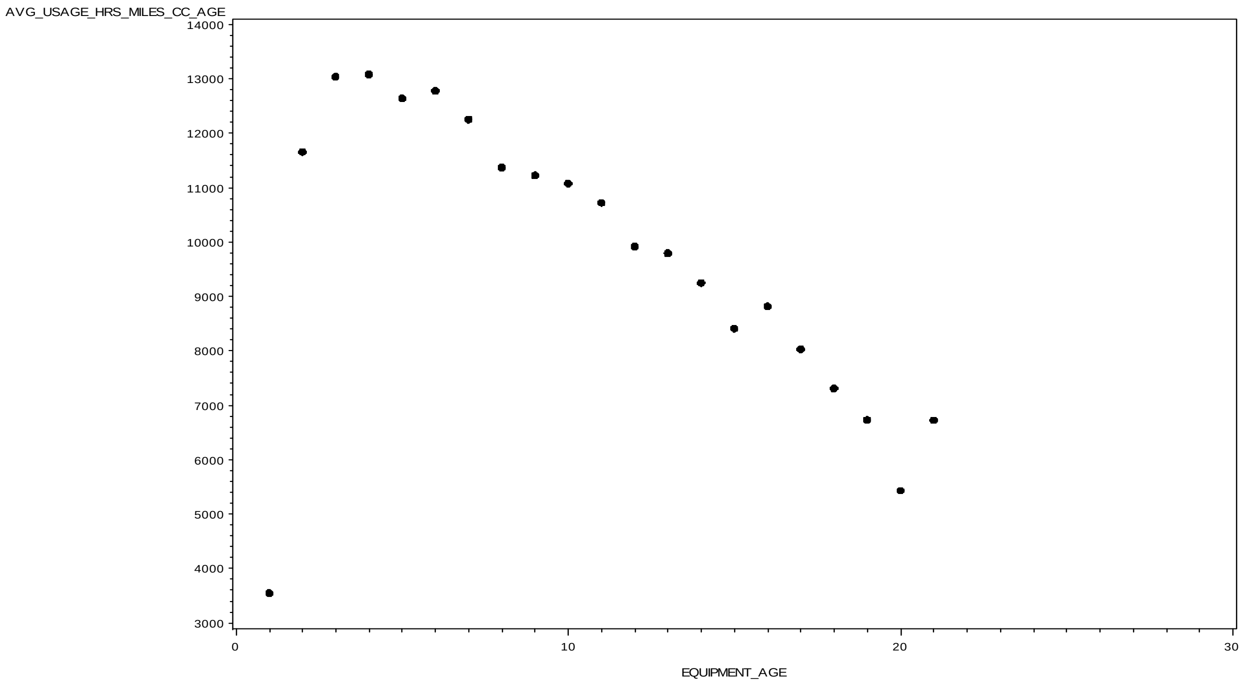


Figure 8.10: Average Usage Miles vs. Equipment Age

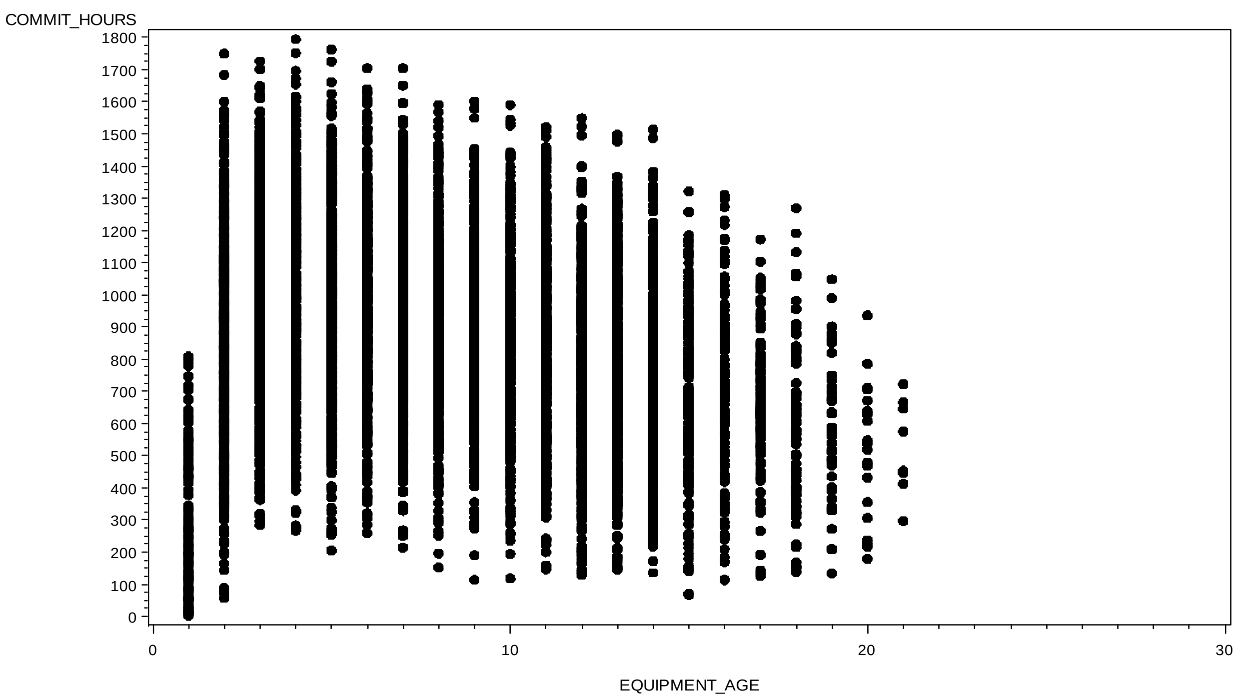


Figure 8.11: Commit Hours vs. Equipment Age

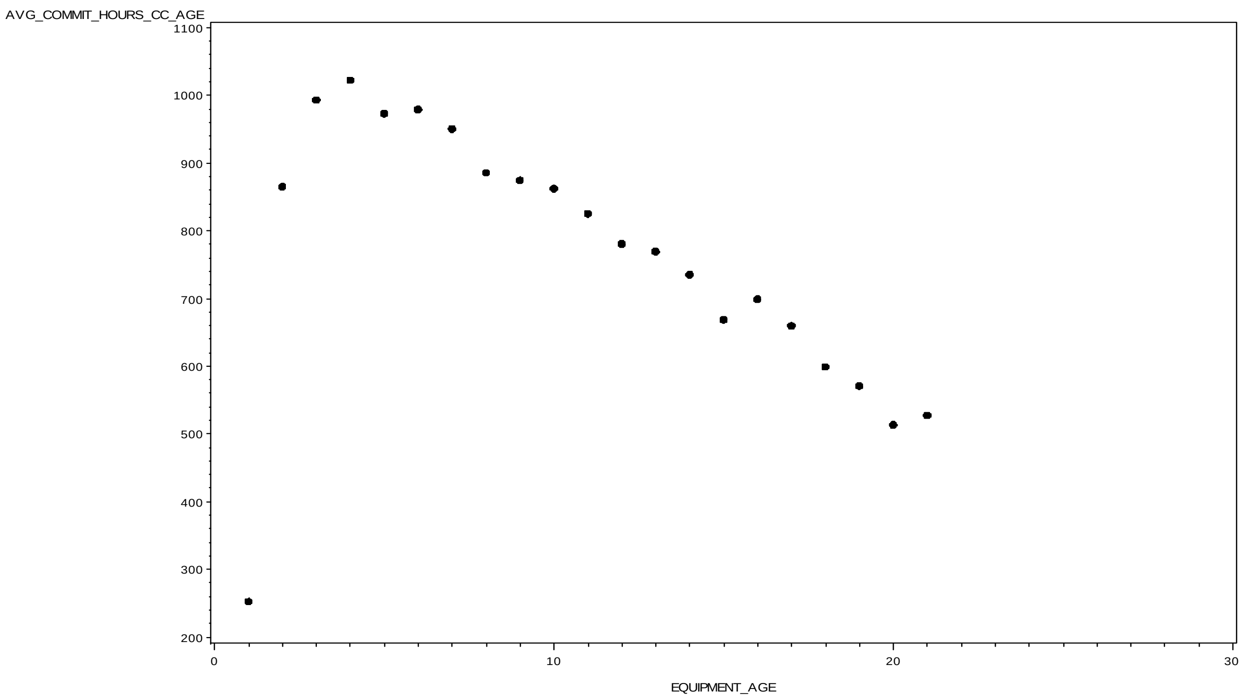


Figure 8.12: Average Commit Hours vs. Equipment Age

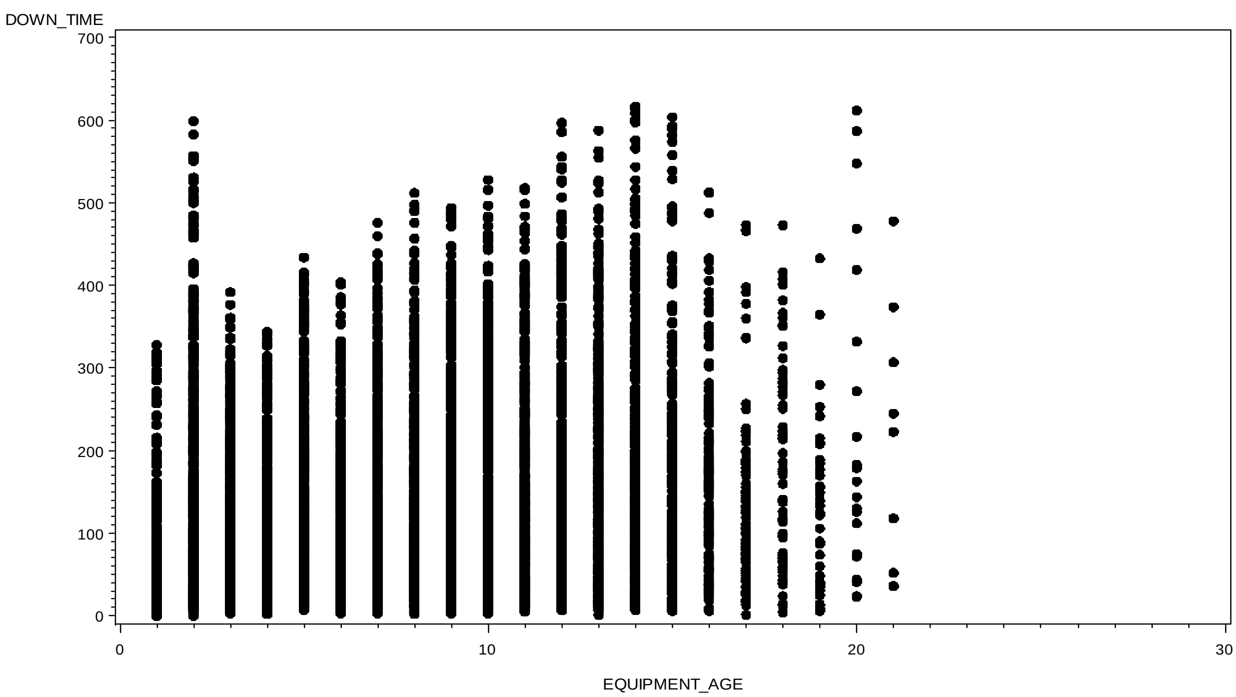


Figure 8.13: Down Time vs. Equipment Age

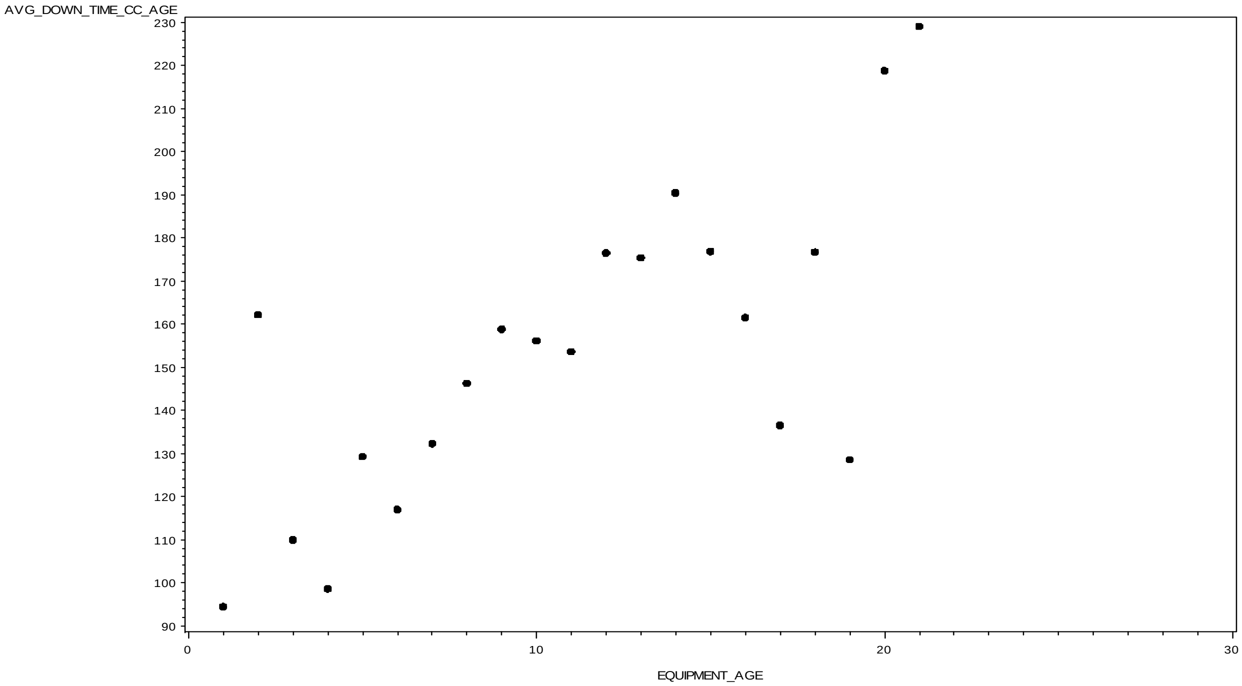


Figure 8.14: Average Down Time vs. Equipment Age

8.2.3 Cost Estimation and Forecasting Model Performance

As for the cost estimation and forecasting model performance, extensive modeling experiments show that nonlinear models appear to outperform linear models (as discussed in section 6.3.2) in most cases for almost all classcodes. However, which nonlinear model type performs better than others will depend upon the specific classcode chosen and dependent variables included in the model. This clearly suggests the benefits and flexibility of the developed SAS macro codes which automate the model selection process.

8.3 DDP Optimization Results

It should be noted that the developed solution methodology in this report is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles both with and 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 (see sections 8.3 and 8.4); 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 (see section 8.5). Also, it should be noted that all numerical results are essentially dependent upon the specific classcode chosen. However, after comprehensive testing it is found that numerical results of all classcodes 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 classcodes, i.e., 420010 and 520020, as an example for the light vehicle and heavy vehicle respectively. Related characteristics are discussed as follows.

8.3.1 Solution Computational Time

The computational time of the DDP-based ERO software for all classcodes was examined. It was found that the computational time is very uniform and it takes an average of 10 seconds for the ERO software to provide the best optimized decision for each classcode. 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 "Current Trend" or "Equal Utilization" approach.

8.3.2 Solution Quality Comparisons and Result Analyses

A comparison of the solution quality for the DDP-based ERO software (optimization solution) and the current replacement criteria (benchmark) for classcodes 420010 and 520020 is given in Table 8.1. The optimization solutions include both "Current Trend" and "Equal Mileage" scenarios. As can be seen, the objective function values (represented in $ value) are smaller (more desirable) for the DDP-based ERO software (optimization solution) than the current replacement criteria (benchmark solution) for both classcodes under both scenarios. This is expected because the DDP solution algorithm ensures that all solutions (paths) are explored by solving backward (which of course also includes the current purely experience-based replacement benchmark solution) and can therefore guarantee 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). Therefore, the optimal objective function value in the former case is always less than that in the latter case.

Also as can be seen from Table 8.1 using classcode 420010 with the "current trend" approach as an example, the best optimized decision is to replace the equipment 4 times over the 20 year window while the current benchmark rules recommends a different replacement solution (keep it for 9 years and replace it at the end of 10th year). Obviously, these two solutions are quite different from each other and the results indicate that using the developed DDP-based ERO software can significantly improve the replacement procedures and can result in substantial cost savings every year. Specifically, for classcode 420010, it is about $4,728.87/20 = $236.44 per year and for classcode 520020, it is $1651.03/20 = $82.55 per year. The average of the cost savings for these two classcode will be ($236.44 + $82.55)/2 = $159.50 per year. Considering there are 194 classcodes used by TxDOT and on average each classcode includes 84 pieces of equipment, a cost savings of $159.50*194*84 = $2,599,171.26 might be expected. As can also be seen from Table 8.1, an even larger cost savings of $4,449,113.55 for the "equal mileage" approach can be estimated using the same calculation method. Therefore, one might expect a cost savings of as much as two million dollars annually for the agency for either approach.

Table 8.1: Solution Quality Comparisons between the DDP Optimized Solution and the Current Benchmark Solution for Classcodes 420010 and 520020 under "Current Trend" and "Equal Mileage" Scenarios

		Year	Cost Current Trend				Cost Equal Mileage			
			DDP Solution		Benchmark Solution		DDP Solution		Benchmark Solution	
			Decision	Cost	Decision	Cost	Decision	Cost	Decision	Cost
Classcode	420010	1	K	$2,881.39	K	$2,881.39	K	$2,368.04	K	$2,368.04
		2	R	$9,050.29	K	$3,320.66	K	$2,618.53	K	$2,618.53
		3	K	$2,881.39	K	$3,782.13	K	$2,895.52	K	$2,895.52
		4	K	$3,320.66	K	$4,256.11	K	$3,201.82	K	$3,201.82
		5	K	$3,782.13	K	$4,732.92	R	$15,863.04	K	$3,540.51
		6	K	$4,256.11	K	$5,202.88	K	$2,368.04	K	$3,915.03
		7	R	$17,989.34	K	$5,656.32	K	$2,618.53	K	$4,329.16
		8	K	$2,881.39	K	$6,083.55	K	$2,895.52	K	$4,787.11
		9	K	$3,320.66	K	$6,474.89	K	$3,201.82	K	$5,293.49
		10	K	$3,782.13	R	$25,673.63	K	$3,540.51	R	$24,706.41
		11	K	$4,256.11	K	$2,881.39	K	$3,915.03	K	$2,368.04
		12	K	$4,732.92	K	$3,320.66	R	$21,714.35	K	$2,618.53
		13	R	$21,887.57	K	$3,782.13	K	$2,368.04	K	$2,895.52
		14	K	$2,881.39	K	$4,256.11	K	$2,618.53	K	$3,201.82
		15	K	$3,320.66	K	$4,732.92	K	$2,895.52	K	$3,540.51
		16	K	$3,782.13	K	$5,202.88	K	$3,201.82	K	$3,915.03
		17	K	$4,256.11	K	$5,656.32	K	$3,540.51	K	$4,329.16
		18	K	$4,732.92	K	$6,083.55	K	$3,915.03	K	$4,787.11
		19	K	$5,202.88	K	$6,474.89	K	$4,329.16	K	$5,293.49
		20	R	$26,202.97	R	$29,674.69	R	$26,238.13	R	$28,707.47
			Total	$135,401.15	Total	$140,130.02	Total	$116,307.49	Total	$119,312.30
			Cost Savings	$4,728.87			Cost Savings	$3,004.81		
	520020	1	K	$1,865.53	K	$1,865.53	K	$820.84	K	$820.84
		2	K	$2,915.71	K	$2,915.71	K	$1,031.38	K	$1,031.38
		3	K	$3,916.86	K	$3,916.86	K	$1,295.92	K	$1,295.92
		4	K	$4,864.60	K	$4,864.60	K	$1,628.32	K	$1,628.32
		5	K	$5,754.55	K	$5,754.55	K	$2,045.97	K	$2,045.97
		6	K	$6,582.32	K	$6,582.32	K	$2,570.75	K	$2,570.75
		7	K	$7,343.55	K	$7,343.55	K	$3,230.14	K	$3,230.14
		8	K	$8,033.85	K	$8,033.85	K	$4,058.65	K	$4,058.65
		9	R	$47,607.00	K	$8,648.84	K	$5,099.67	K	$5,099.67
		10	K	$1,865.53	K	$9,184.14	R	$47,180.66	K	$6,407.71
		11	K	$2,915.71	R	$52,129.15	K	$820.84	K	$8,051.25
		12	K	$3,916.86	K	$1,865.53	K	$1,031.38	R	$54,248.30
		13	K	$4,864.60	K	$2,915.71	K	$1,295.92	K	$820.84
		14	K	$5,754.55	K	$3,916.86	K	$1,628.32	K	$1,031.38
		15	K	$6,582.32	K	$4,864.60	K	$2,045.97	K	$1,295.92
		16	K	$7,343.55	K	$5,754.55	K	$2,570.75	K	$1,628.32
		17	K	$8,033.85	K	$6,582.32	K	$3,230.14	K	$2,045.97
		18	K	$8,648.84	K	$7,343.55	K	$4,058.65	K	$2,570.75
		19	K	$9,184.14	K	$8,033.85	K	$5,099.67	K	$3,230.14
		20	R	$60,198.47	R	$57,327.35	R	$56,080.19	R	$51,627.85
			Total	$208,192.39	Total	$209,843.42	Total	$146,824.13	Total	$154,740.07
			Cost Savings	$1,651.03			Cost Savings	$7,915.94		

8.3.3 Solution Implications

In addition, from Table 8.1 the results seem to suggest relatively major changes to replacement policies. Comprehensive testing indicates that both the optimal keep/replacement decision and predicted cost savings largely depend upon the salvage value calculation, the annual operating and maintenance cost, and particularly the purchase cost forecasting that comes from the SAS macro data analyzer and cleaner (Fan et al, 2011a).

However, after comprehensive testing and results analyses, it seems that if the adjusted purchase cost is increasing, the ERO solution suggests early replacement for light vehicles and late replacement for heavy vehicles. This might be expected because heavy vehicles are normally much more expensive, depreciate less rapidly, and therefore will be more desirable to keep a little longer than light vehicles. On the other hand, light vehicles are generally less expensive, depreciate more rapidly, and therefore it will be more desirable to replace as early as possible in order to minimize the total costs. However, if the adjusted purchase cost is flat and either including or excluding the fuel cost as part of the decision process, the ERO solution generally suggests as late as possible replacement for both light and heavy vehicles. More comprehensive testing on the impact of uncertain forecasted purchase cost on the ERO decisions is currently under way.

8.4 SDP Optimization Results

8.4.1 Solution Computational Time

The computational time of the SDP-based ERO software for all classcodes was also examined. It was found that the computational time is very uniform for the SDP 2-Level approach and it takes an average of 10 seconds for the ERO software to provide the best optimized decision for each classcode, which is almost identical to the DDP approach (Fan et al, 2011b). As a result, 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. However, the SDP 3-Level approach appears to be less uniform and most classcodes takes 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 classcode with probabilistic vehicle utilization. It therefore takes a total of about 97 minutes to loop through all (i.e., 194) classcodes 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. Such results for the SDP approach for each individual and all classcodes clearly indicate the need to conduct the scenario reduction treatment in the SDP state-space as shown in section 7.3.2 and also show its immediate effectiveness in enforcing the linear (instead of exponential) growth in both the computer memory and solution computation time.

8.4.2 Solution Quality Comparisons and Results Analyses

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 given in Table 8.2. As can be seen, the objective function values (represented in $ value) for each approach are smaller (more desirable) than for the corresponding benchmark solutions for both classcodes. This is expected because each 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).

Table 8.2: Solution Quality Comparisons between the SDP and DDP Optimized Solutions and the Current Benchmark Solution for ClassCodes 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		

In addition, one may notice that 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 classcode-level cost/mileage forecast for all future years to calculate the benchmark decision year, while both SDP approaches generate and use cost/mileage forecasts for each individual and all the vehicle utilization levels (low-high for 2-Level, or low-medium-high for 3-Level) and their associate 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 also see from Table 8.2, 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 suggests replacement at years 10 and 20 only. While the SDP 3-Level solution and the DDP solution offer similar replacement strategy 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. For classcode 520020 the SDP 2-level solution estimates the cost savings with replacement on years 6, 13, and 20 of $8,631.65/20 = $431.58 per year, which is much greater than either the DDP or the SDP 3-level solutions. The average of the cost savings for these two classcodes will be ($273.22 + $431.58)/2 = $352.40 per year. 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. As can also be seen from Table 8.2, a relatively smaller cost savings of $2,506,389.98 for the SDP 3-Level approach can be estimated using the same calculation method. Therefore, one might expect a cost savings of several million dollars annually for the agency for the SDP approaches.

8.4.3 SDP vs. DDP

After conducting comprehensive testing, all three approaches have produced promising results and can yield significant cost savings compared to the current TxDOT benchmark decisions. While DDP is generally more stable and reliable in terms of its cost forecasting quality because of the relatively abundant aggregate data for each classcode, the SDP approaches are set up to allow the user (i.e., the fleet manager) to obtain more realistic results if a large enough and reliable data set exists for each classcode at different vehicle utilization levels. In other words, while using the same data, DDP generates the classcode-level cost/mileage forecast for each equipment age using all the data and SDP will need to partition the same data into separate vehicle utilization levels and generate the cost/mileage forecasts and associate probability distributions for each individual and all levels for each equipment age. In this regard, the SDP produces more realistic/reliable results when sufficient data is available. Such sufficient data currently exists for only certain classcodes, and the others will require additional data in the future. 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 accumulates.

8.5 Solution Generation under Annual Budget Constraints

Sections 8.3 and 8.4 show the numerical results and provides a general guide for the equipment keep/replacement decisions (i.e., how many years to keep) for two particular classcodes containing brand-new equipment without considering any budget constraints. In so doing, the annual budget constraints, which may exist in the real world for government agencies and private fleet sectors, are not explicitly considered. However the developed solution methodology in this report can also be used to select the equipment units for annual replacement based on the annual budget constraints and possibly some other constraints specified by the fleet manager. The classcode 420020 shown in Table 8.2 and section 8.4.2 is a good example of why such additional constraints are needed. As mentioned previously the SDP 2-Level solution for this classcode suggests replacement on years 1 and 2; however, replacing any one- or two-year old equipment unit does not make much sense intuitively. To circumvent this issue, the TxDOT fleet manager made the recommendation that the actual equipment replacement age should not be different from the current TxDOT benchmark replacement rule by more or less than 3 years. To solve the ERO problem under such constraints, the following steps are undertaken.

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 replacing 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, based on these cost inputs, a second round of optimization (i.e., the Knapsack programming), which can explicitly consider any annual budget constraints and possibly some other constraints specified by the fleet manager, is used to select the equipment units for annual replacement from a solution space that consists of all 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 costs increased due to delay for equipment replacement) in order to embody a mixture of both TxDOT's short-term and long-term interests. Preliminary result indicates that a significant amount of cost savings can be estimated by using the developed solution methodology when using an annual budget of 15 million dollars for the TxDOT's current TERM data.

8.6 Summary

This chapter discusses some comprehensive statistical analyses, DDP and SDP optimization results using the real world TxDOT TERM data. Preliminary testing indicates that a significant amount of cost savings (i.e. millions of dollars) can be estimated annually by using the developed ERO solution software for brand-new or used equipment units with or without annual budget consideration for the TxDOT.

Chapter 9. Summary and Conclusions

9.1 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 in retaining their value may exist in the marketplace and be available for replacement. For this reason public and private agencies that maintain fleets of vehicles and/or specialized equipment must periodically decide when to replace vehicles composing their fleet. These equipment replacement decisions are usually based upon a desire to minimize fleet costs and are often motivated by the conditions of deterioration and technological changes (Hartman, 2005; Hartman, 2008).

The primary function of this report is to develop an ERO decision tool that can be effectively used as part of a long-range fleet replacement plan to replace the right equipment at the right time and at the lowest overall cost. To accomplish this task, a theoretically sound and practically feasible ERO methodology has been developed to accommodate specific TxDOT needs. It is expected that a significant amount of money will be saved (Fan et al., 2011a; 2011b; 2011c).

The rest of this chapter is organized as follows. Section 9.2 provides a brief review of the methods used to solve the ERO problem as well as the features included in the developed ERO software. Section 9.3 details the directions that should be taken in future research in order to improve the ERO decision making process.

9.2 Summary and Conclusions

This report has described the ERO problem as it might apply to agencies or companies that maintain vehicle fleets. An extensive review of the current literature and state-of-the-art/practices concerning the ERO problem has been conducted. Existing ERO status within the state of Texas, consulting companies, and other state DOTs has been investigated. The current state of ERO research is reviewed and four different approaches for solving the ERO problem are discussed, these are the EAC approach, the Experience/Rule based approach, the DDP approach, and the SDP approach. It is determined that the ERO problem can be formulated as an ILP model in which the objective is to minimize the total cost and the decisions to be made are to either replace or retain the unit of equipment at the beginning of each year.

The developed solution framework for the ERO problem in this report consists of three main components: 1) A Java based GUI that takes parameters selected by users, displays the final results of the optimization, and coordinates the other two components; 2) A SAS Macro based Data Cleaner and Analyzer, which undertakes the tasks of raw data reading, cleaning and analyzing, as well as cost estimation & forecasting; and 3) A DP-based optimization engine that minimizes the total cost over a defined horizon.

In particular, the SAS Macro Data Cleaner and Analyzer takes the user specified options through the Java GUI and undertakes a series of steps when an optimization is run. In such steps, raw TERM data is read and errors & outliers are removed, after which cost estimating and forecasting are performed. Several intermediate SAS tables are generated for the user's review, and several internal tables (some dealing with the historic equipment purchase cost data and purchase cost forecasts, and the others containing the O&M cost, the salvage value, and the usage information for the classcode for each equipment age) are generated and passed on to the optimization engine. Once the DP-based optimization engine (also written in Java code) receives the internal tables generated by the SAS macro codes it executes the DP-based optimization approaches and makes the best keep/replacement optimization decision. This decision is then passed on to the Java-based GUI for the users to review or save.

It should be noted that the proposed DP solution algorithms have been implemented and solved via backward recursion and Java based DP solution software is developed to minimize the total costs. The software developed can recommend an optimized solution whether to retain or replace a unit of equipment based on the equipment class, age, mileage, salvage value, and replacement cost from SAS macro codes. The DP-based optimization engine has been formulated for both the DDP approach and the SDP approach; Bellman's and Wagner's formulations have also been incorporated to solve the ERO problem. The DDP solution approach optimizes the ERO decisions over a given time horizon based on the expected purchase cost, annual operating & maintenance cost, and salvage value. Due to uncertainty in real operations, these expected equipment utilization costs may not be realized, for such cases, the SDP solution approach has also been developed with uncertainty in asset utilization. Effective scenario reduction treatments are developed to resolve the "curse of dimensionality" issue in the state-space domain that is inherent to the DP method to ensure that the computer memory and solution computational time required will not increase exponentially with the increase in time horizon.

Additionally, the developed ERO solution methodology is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles both with and without annual budget considerations. Most importantly, knapsack programming used in the second round of optimization can explicitly consider any annual budget constraints and select the equipment units for annual replacement from a solution space composed of all the equipment units that are eligible for replacement.

The developed ERO software contains many features and options that can be employed by the user to get the results that are best suited to his/her specific needs. Optimization can be run on a single classcode, a specific classcode, or all classcodes for which there is available data and for a specific equipment unit, brand new equipment units, or all equipment units. The software allows the user to specify budget constraints, the time window, the inflation rate, the cost of money, and the desired number of years to delay the replacement of the selected equipment. The user can choose between two different cost forecasting approaches, Cost Current Trend or Cost Equal Mileage; and several different solution approaches; DDP, SDP 2-Level, or SDP 3-Level, and Bellman or Wagner. The user can choose to run the software using SAS automatically generated cost data or use the Editable cost data that they have provided manually at the beginning of each year, and users can selectively "Clean the data." Finally, users can add new annual TERM data at the beginning of each year and make dynamic keep/replacement decisions for any chosen classcode or equipment units.

Comprehensive testing and statistical analyses have been conducted and numerical results show several trends that are consistent across classcodes for the majority of the TERM data.

Firstly, as model year increases, the non-adjusted original total purchase cost increases noticeably. This is probably due to the fact that as the technology advances, equipment normally gets more expensive and therefore, the purchase cost in the absolute dollar values increases along the years. However, accounting for economy-dependent inflation rate adds more complexities and therefore will make the prediction for the inflation-adjusted total purchase cost less reliable and unpredictable. After adjustment the total purchase cost seems to decrease initially and then increase slightly into the future although the pattern is not very clear. Secondly, as equipment age increases several things happen; the equipment utilization decreases, the commit hours decrease, the total OM cost per mile/hour increases, and the down time seems to stay flat. This might be due to the fact that as equipment gets older, the risk of equipment being down generally increases and the down time might also increase assuming equal mileage being used. On the other hand however, as equipment ages, the equipment utilization decreases. These two effects cancel each other and that may explain why the down time almost stays the same as equipment ages.

After comprehensive testing and analyses some implications can also be seen about the cost estimation and forecasting model performance as well as the DDP and SDP optimization performance. While nonlinear models seem to outperform linear models in most cases, which nonlinear model type performs better than others will depend upon the specific classcode chosen and the dependent variables included in the model. The developed SAS macro codes automate the model selection process and have the flexibility to find the best model type for the specific classcode chosen. Furthermore, all testing indicates that the DP-based optimization engine will perform very efficiently and effectively. The computational time is very uniform for both the DDP solution approach and the SDP 2-Level solution approach, which takes an average of 10 seconds for the ERO software to provide the best optimized decision for each classcode. It takes a total of about 32 minutes to loop through all (i.e., 194) classcodes and output all optimized solutions. The SDP 3-Level solution approach, however, is less uniform and takes approximately 30 seconds per classcode and a total of nearly 97 minutes to loop through all classcodes.

Extensive testing of the TERM data also indicates that the ERO decision, for DDP, SDP 2-Level and SDP 3-Level approaches using either Bellman’s or Wagner’s formulations, gives a smaller (more desirable) cost than the current benchmark solution strategy. This is expected because the DP-based solution algorithm ensures that all solution paths are explored (which of course also includes the current purely experience-based replacement benchmark solution) by solving backward and can therefore guarantee 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).

Additionally, it seems that if the adjusted purchase cost is increasing, the ERO solution suggests early replacement for light vehicles and late replacement for heavy vehicles. This might be expected because heavy vehicles are normally much more expensive than light vehicles and generally depreciate less rapidly than light vehicles. It therefore will be more desirable to keep heavy vehicles longer than light vehicles which are replaced as early as possible in order to minimize the total costs. However, if the adjusted purchase cost is flat and either including or excluding the fuel cost as part of the decision process, the ERO solution generally suggests as late as possible replacement for both light and heavy vehicles. In this regard more comprehensive testing is currently under way.

As mentioned earlier, all three approaches have produced promising results and can yield significant cost savings compared to the current TxDOT benchmark decisions. While DDP is generally more stable and reliable in terms of its cost forecasting quality because of the relatively abundant aggregate data for each classcode, the SDP approaches are set up to allow the user to obtain more realistic/reliable results when sufficient data is available. 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 accumulates.

Most importantly, the developed solution methodology in this report can be used to select the equipment units for replacement based on the annual budget constraints by the fleet manager. To solve the ERO problem under such 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 solution to the minimum total cost incurred when delaying replacing 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. Based on these cost inputs, the developed Knapsack programming is used to select the equipment units for annual replacement from a solution space that consists of all equipment units that are eligible for replacement. The main objective of this Knapsack programming is to minimize the total costs increased due to delay for equipment replacement in order to embody a mixture of both TxDOT's short-term and long-term interests. Preliminary result indicates that a significant amount of cost savings can be estimated by using the developed solution methodology when using an annual budget of 15 million dollars for the TxDOT's current TERM data.

9.3 Directions for Future Research

The formulated ERO model, as well as the developed Bellman's and Wagner's solution approaches, appears to be both theoretically sound and practically feasible. The DP-based solution software optimizes the ERO decisions over a given time horizon based on the expected purchase cost, annual operating & maintenance cost, and salvage value. Significant cost savings can be estimated by using the developed ERO software.

The developed DDP approach assumes that these costs/values are constant or predetermined. It should be noted that while the DDP approach works well for nearly all classcodes. However, due to uncertainty in real operations, these expected equipment utilization costs may not be realized, in such cases, the developed SDP approach may be preferred. However, the SDP approach currently requires additional historic data for many classcodes and the lack of a large enough and reliable data set for some classcode/equipment units may prevent the SDP software from generating the most reliable solutions possible. It is anticipated as the data collection effort accumulates, more reliable results can be thus achieved for the SDP approach. Future research will be directed toward these ends with further insight provided for applying and solving real world instances of the ERO problem under uncertainties.

In addition, the impact of the uncertain future purchase cost and the down time costs on the ERO keep/replacement decision and its total cost is currently under scrutiny. Additionally, advanced and realistic estimation and forecasting methods will be developed for the annual O&M cost and mileage. More computational insights into the ERO problem and the solution implications for each individual and all classcodes will be forthcoming and presented as this line of research matures.

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Appendix A: Practical Guidelines on Equipment Replacement Optimization

CHAPTER A.1: INTRODUCTION

A.1.1 WHAT IS EQUIPMENT REPLACEMENT OPTIMIZATION?

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 in retaining their value may exist in the marketplace and be available for replacement. The conditions of deterioration and technological changes, either separately or together, often motivate equipment replacement decisions (Hartman, 2005; Hartman, 2008). According to the Texas Department of Transportation (TxDOT) (TERM, 2004), 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 (TERM, 2004). Equipment Replacement Optimization (ERO) can improve TxDOT's replacement procedures and potentially save millions of dollars.

Substantial cost savings with fleet management has been documented in management science literature. For example, a 1983 Interfaces article (Waddell, 1983) discussed how Phillips Petroleum saved $90,000 annually by implementing an improved system for a fleet of 5300 vehicles. Scaling up to the TxDOT fleet, the corresponding savings would be around $350,000 in 2008 dollars. Similar savings were reported in presentations made by Mercury Associates (Mercury Associates, 2002; 2005; 2007).

The equipment replacement optimization effort is also extremely important in the context of overall fleet management efforts. For example, the best equipment replacement decision tool in the world may not be very useful if there is no funding available to purchase new vehicles to replace the old ones. The ERO decision tool can be effectively used as part of a long-range fleet replacement plan that can estimate the future budget required to meet predicted future replacement needs. The primary function of equipment managers is to replace the right equipment at the right time and at the lowest overall cost. To accomplish this task, a theoretically sound and practically feasible equipment replacement optimization methodology has been developed to accommodate specific TxDOT needs. It is expected that a significant amount of money will thus be saved.

A.1.2 HOW DOES EQUIPMENT REPLACEMENT OPTIMIZATION WORK?

Figure A.1.1 provides a flow chart of the developed solution framework for the ERO problem, which consists of three main components: 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 Dynamic Programming (DP)-based optimization engine that minimizes the total cost over a defined horizon; and 3) A Java based Graphical User Interface

(GUI) that takes parameters and inputs selected by users and coordinates the Optimization Engine and SAS Macro Data Cleaner and Analyzer (Fan et al, 2011a).

As one can see, the GUI has been developed using Java programming language to interact with the software users such as the fleet manager. It takes all inputs from users, processes them using Java codes, and calls SAS macro codes by passing on the user-specified classcode/equipment units with other options. The SAS macro codes then process the raw data corresponding to the user's inputs and his/her requirements. Raw TERM data is read and errors and outliers are removed. Cost estimating and forecasting as well as data generating are performed. Several intermediate SAS tables are generated for the user's review and passed on to the optimization engine, some being the equipment purchase cost forecasts for each decision year over a defined future time horizon (which depend on the equipment model year), and others containing the annual/accumulative O&M cost, the salvage value at the end of each decision year, and the annual/ accumulative mileage information for the classcode for each equipment age. After receiving these tables from the SAS macro codes, the optimization engine (also written in Java code) executes the DP-based optimization approaches and makes the best keep/replacement optimization decision. The knapsack programming optimization method will be used to solve the ERO problem under budget constraint to account for the optimal replacement of multiple equipment units. The decision results are either presented to the software user (i.e., the fleet manager) on screen or they can be saved and viewed in an EXCEL format through the GUI (Fan et al, 2011a).

It should be noted that we have implemented the proposed DP solution algorithms via backward recursion and developed Java based DP solution software to minimize the total costs. The software developed can recommend an optimized solution whether to retain or replace a unit of equipment based on the equipment class, age, mileage, salvage value, and replacement cost from SAS macro codes. In particular, it should be mentioned that the developed ERO solution methodology in this project is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles, both with and without annual budget considerations (all will be discussed in Chapter A.4). Furthermore, the developed software system is very user-friendly and designed so that it can be easily used by non-technical personnel (to evaluate individual district units against a class) and by technical division personnel (Fleet Manager) to develop optimal aggregate classcode replacement cycles (Fan et al, 2011a).

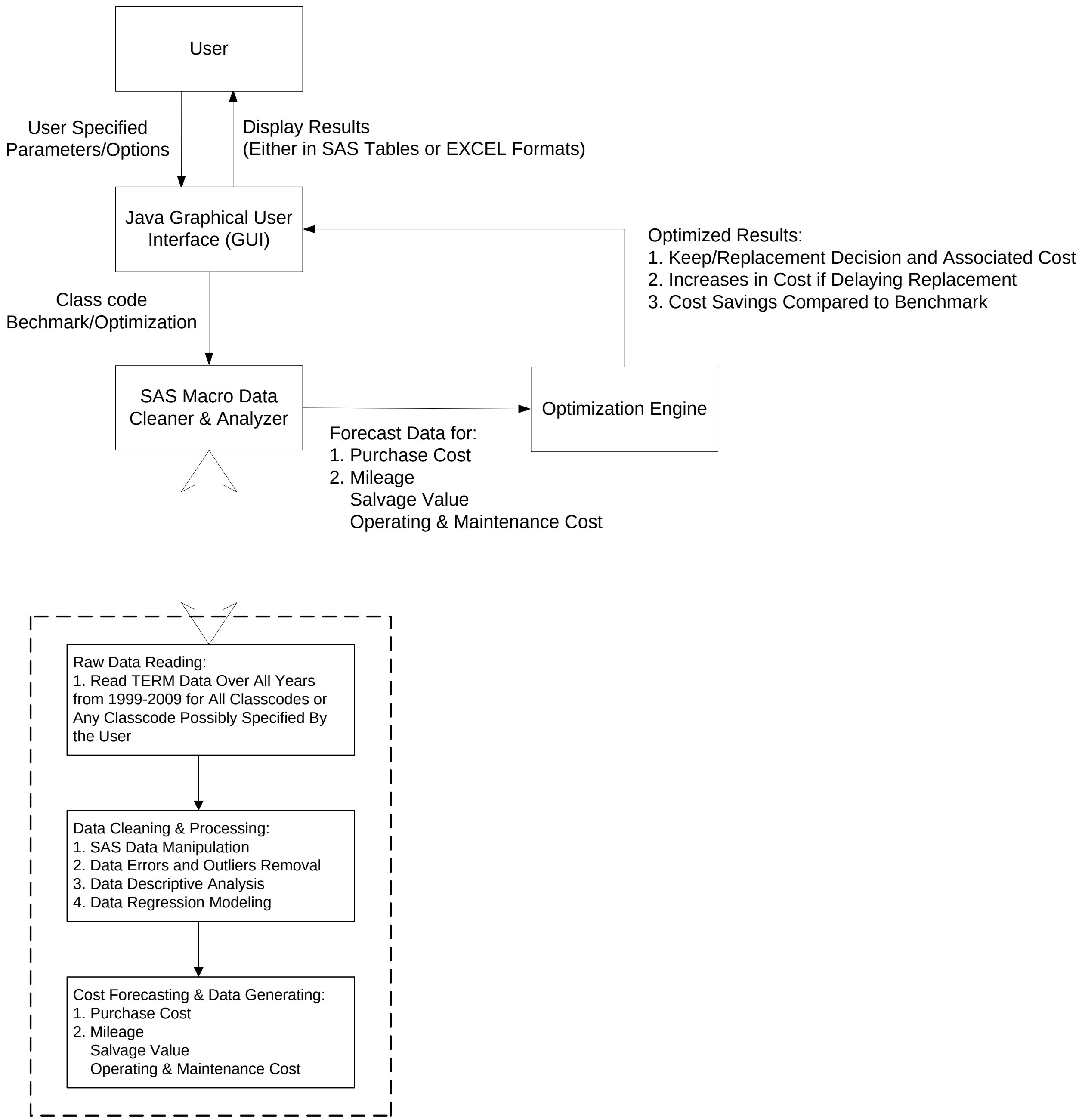


Figure A.0.1 Flow Chart of the Developed DP-based Equipment Replacement Optimization Solution Methodology

CHAPTER A.2: INSTALLATION

A.2.1 SYSTEM REQUIREMENTS

The software is designed to run on systems with Microsoft™ XP or better. The recommended settings are as follows:

- 2.20 GHz Processor
- 1.96 GB of RAM
- The most recent version of Java Runtime Environment
- Full version of licensed SAS software must be installed

A.2.2 DOWNLOAD AND INSTALL JAVA RUNTIME ENVIRONMENT

The software requires that Java Runtime Environment be installed on the computer. This process requires the user to download an executable file that includes all the files needed for the complete installation. The user does not need to remain connected to the Internet during the installation. The file can also be copied to a computer that is not connected to the Internet.

- Go to the manual download page: http://java.com/en/download/manual.jsp
- Click on **Windows 7, XP Offline.**
- When the file download dialog box appears, click **Save** to download the file to the user's local system.
  *Tip: Save the file to a known location on the user's computer, for example, to the user's desktop.
- Close all applications including the browser.
- Double-click on the saved file to start the installation process.

Figure A.0.2: Java License Agreement

The installation process starts. The installer is presented an option to view the License Agreement. Click the Install button to accept the license terms and to continue with the installation.

During installation, the user may be asked to install additional programs. The installation of these programs is not mandatory. After ensuring that the desired programs are selected (if any), click the Next button to continue the installation.

Figure A.0.3: Installing Java

A few brief dialogs confirm the last steps of the installation process; click Close on the last dialog. Once the installation has finished, the user will need to close and re-open the browser. To test that Java is installed on the user's computer, run this test applet: http://java.com/en/download/help/testvm.xml. The user may have to wait for a few moments before the test is finished.

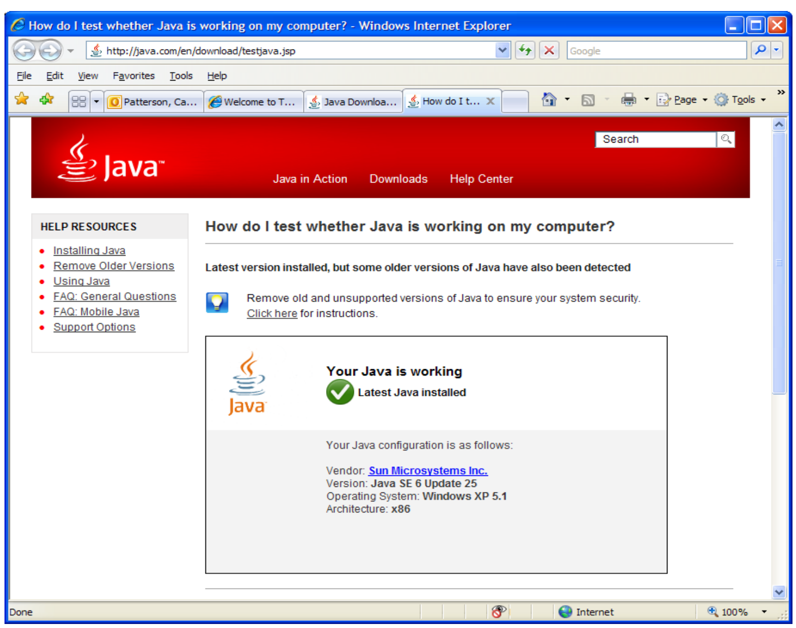


Figure A.0.4: Java Installation Completion Test

A.2.3. DOWNLOAD AND INSTALL JAVA SDK (OPTIONAL)

- Go to the download page: http://www.oracle.com/technetwork/java/javase/downloads/index.html

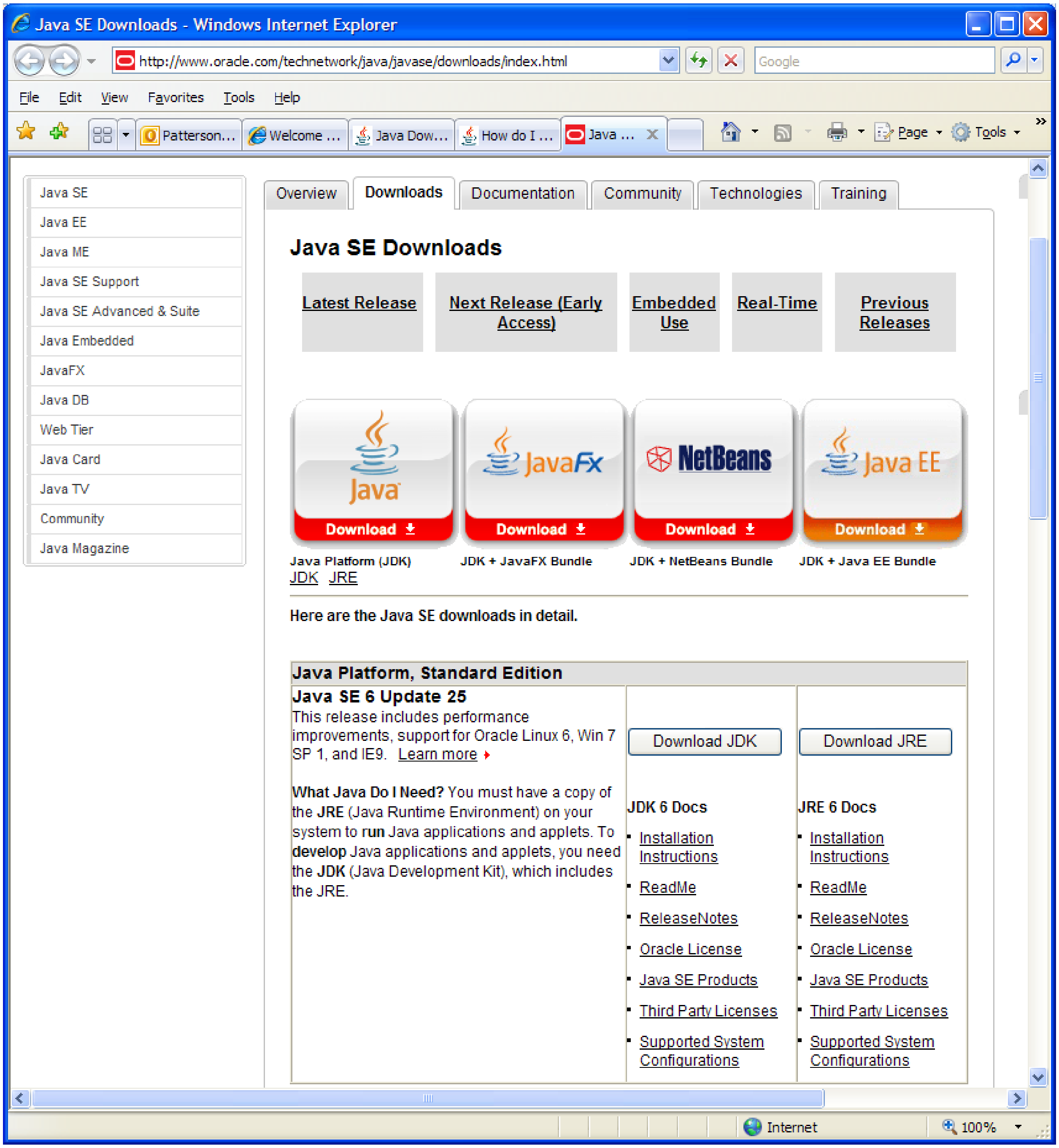


Figure A.0.5: Java Download Page

- Select the 'Download JDK' option button.

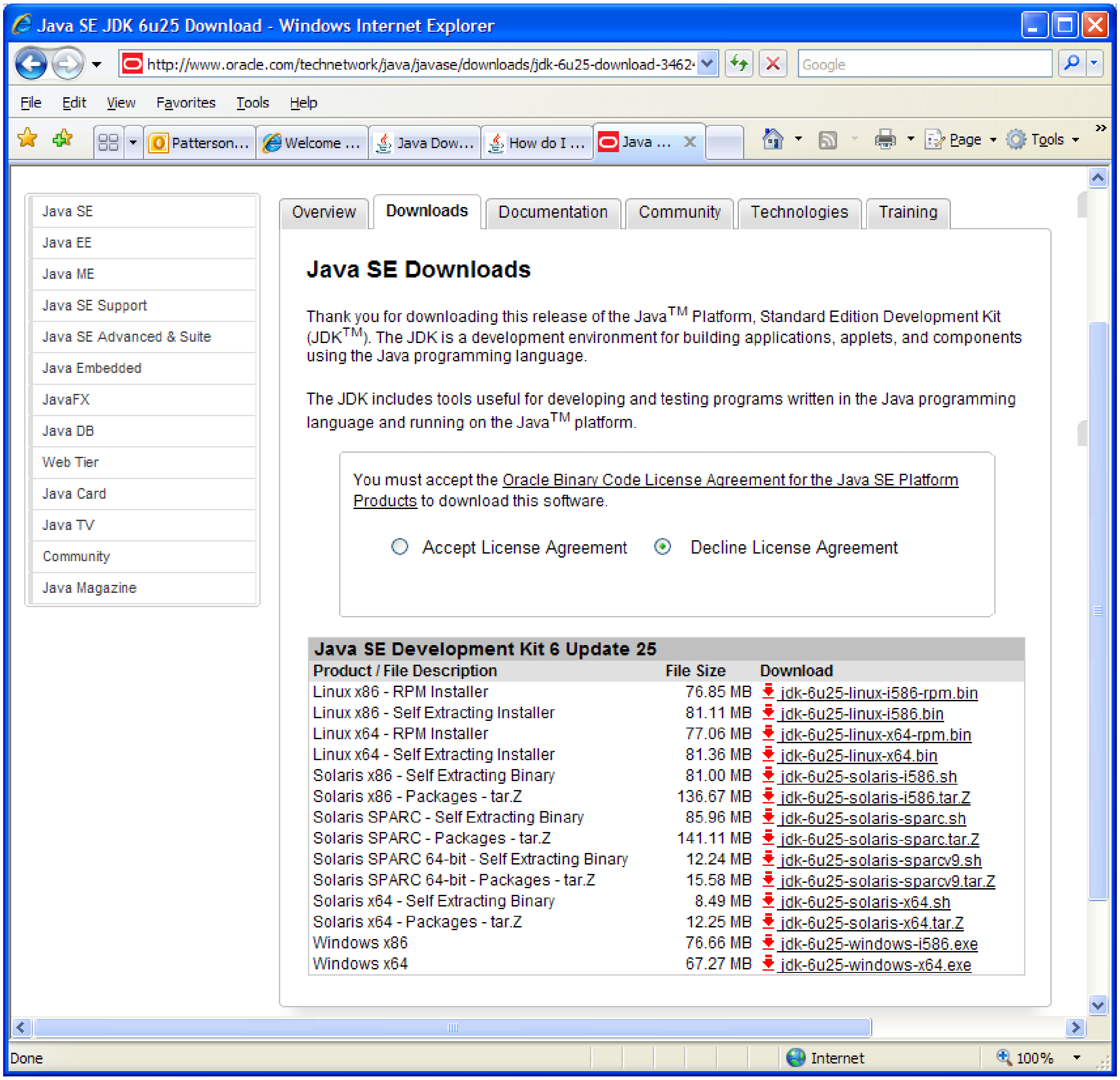


Figure A.0.6: Java License Agreement & Download Page

- Check the checkbox to Accept License Agreement.
- Select the Windows option appropriate to the user's system (option 'Windows x86' is recommended for most systems.)
- When prompted to save the file, choose **run** and wait for the download to finish.
- If prompted with a security warning after the download finishes, choose **run**.

A.2.4 INSTALLING EQUIPMENT REPLACEMENT OPTIMIZATION SOFTWARE

Copy the entire directory to a preferred directory such as C:\ERO. Remember this location. Make sure that the latest "optimizer.jar," "sasmarcr.sas7bcat," "TERM Benchmark Rules" files, and all the annual TERM data files are included in the directory. Note: the file "optimizer.jar" is found in the "\Optimizer\dist" folder and the other two files are in the "\TERM Data\Input" folder as will be mentioned in section A.3.1.1. If a shortcut is desired, see ‘Appendix A.C – FAQ’s, section A.C.1.

CHAPTER A.3 PROGRAM HANDLING

To execute the software, go to the directory in which the software was installed as referenced in section A.2.4. Open the “Optimizer” folder, then open the “dist” folder, and execute the file “Optimizer.jar” by double-clicking it. This should display the Input Interface screen, similar to the one shown in Figure A.3.1. There are two tabs located at the top of this screen, an “Input” tab and an “Options” tab; the software will default to the Input Interface when opened but the user can use these tabs to navigate between the Options Interface, as will be discussed in section A.3.2, and the Input Interface, as will be discussed in section A.3.1. The buttons and fields found on the Input Interface are discussed in the following section.

A.3.1 INPUT

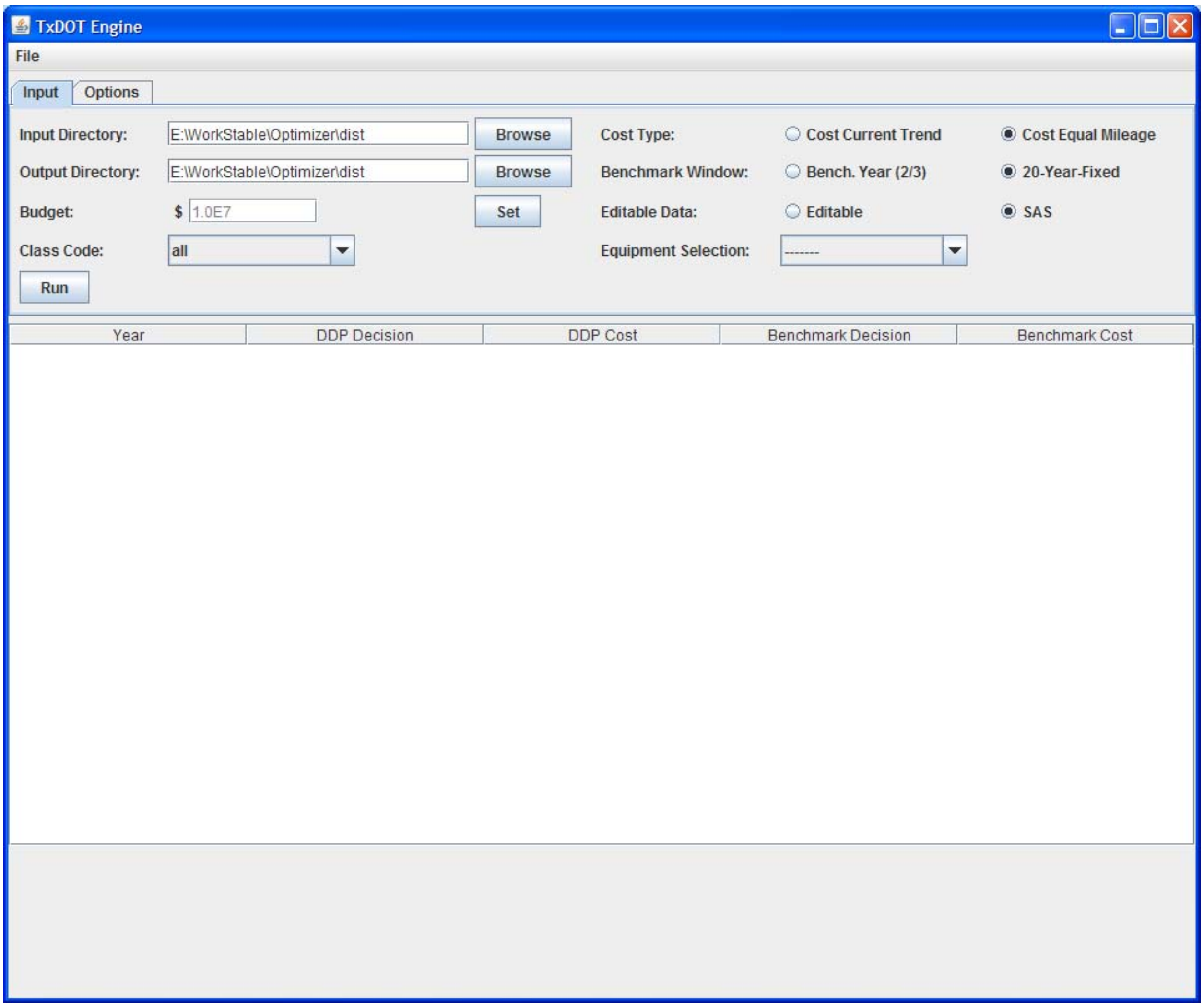


Figure A.0.7: Standard Interface – Input Screen

A.3.1.1 Input Directory

The “Input Directory” field is used to specify where input files (i.e. Raw TERM Data files) for SAS processing will be stored (currently located in folder \TERM Data\Input). These files include the provided (1999 to 2009) annual historic data. For example TERM_1999_Data represents all the cost, mileage, and other information for all classcodes and equipment units for the year 1999, collected under the Texas Equipment Replacement Model (TERM). More annual information can be added, in the same format as the 2009 data, when collected for any future years. The definitions of the data elements can be found in Appendix A.A.

The “Input Directory” field will automatically save the entry used for the last complete optimization run as the default entry to be used for all future runs, until this field is changed by the user. Also located in the input folder must be the TxDOT TERM Benchmark rules file, which is used as TxDOT’s current replacement strategy (TERM, 2004). For more detailed information relating to the benchmark rules for all classcodes, please refer to Appendix A.B.

In addition, many source code files written in the SAS macro have been developed and used to undertake the tasks of TERM raw data reading, cleaning and analyzing, as well as cost estimation and forecasting (Fan et al, 2011a), as presented in the technical report, should already be compiled as a single sasmacro file entitled “sasmacr.sas7bcat” and should be found in this input folder. This file will be essential for the “Optimizer.jar” to run.

Furthermore, at the beginning of each new fiscal year, the software will issue a message through a pop-up window to remind the user to add new TERM data for the past fiscal year. If the new data is not available yet, or the user wants to run optimization before the new data has been introduced, select “No” when asked to dump the new year’s data. In case of any missing TERM data for any of the past years, a similar pop-up window will display a message to inform the user of such missing data. To add additional data at the beginning of each new fiscal year, see Appendix A.C – FAQs, section A.C.5.

A.3.1.2 Output Directory

The “Output Directory” field is used to specify where SAS generated files will be stored (currently located in folder \TERM Data\Output). Several intermediate SAS files are also generated after each optimization run. The three most important of these files provide the historical vehicle usage/cost data for a specific classcode XXXXXX; they are, Term_cost_exp_cur_trend_XXXXXX, Term_cost_exp_eq_mileage_XXXXXX, and Term_usage_merge_all_yr_XXXXXX. These files show all of the historical data for the classcode specified. The first file, Term_cost_exp_cur_trend_XXXXXX, provides information about the annual average mileage and annual average O&M cost by individual equipment age for the “Cost Current Trend” option; and the second file, Term_cost_exp_eq_mileage_XXXXXX, shows the information about the annual average mileage and annual average O&M cost by individual equipment age for the “Cost Equal Mileage” option. The third file, Term_usage_merge_all_yr_XXXXXX, shows data that is used to show the annual average usage information by each fiscal year under the “Cost Current Trend” option. In addition several intermediate Excel tables are generated for the user’s review and they can be found in this folder, as will be described in section A.4.2. These files may be deleted or moved after review if so desired. For further information on the intermediate SAS files see Appendix A.C – FAQs, section A.C.6.

Like the "Input Directory", the "Output Directory" field will also automatically save the entry used for the last complete optimization run as the default entry to be used for all future runs, until this field is changed by the user.

A.3.1.3 Class Code

Two options are available for this field:

A.3.1.3.1. All. If "All" is selected the software loops through all classcodes and gives optimized results individually for all classcodes (either at the all equipment unit level or at the aggregate classcode level only as will be mentioned in section A.3.1.4) that currently exist in the TERM data for the newest year.

A.3.1.3.2. Individual. If an individual classcode is selected (e.g., 001010) the software provides optimized results for that classcode only (either at the all equipment unit level, at the individual equipment unit level, or at the aggregate classcode level only as will be mentioned in section A.3.1.4).

A.3.1.4 Equipment Selection

If the "all" option is selected under the Class Code then there are two options available for the Equipment Selection option: all or ------- (No equipment unit selected).

If an Individual Class Code is selected then there are three options available for the Equipment Selection option: all, individual, or ------- (No equipment unit selected).

In summary, there are five options that can exist for the combined ClassCode/Equipment Selection:

1) INDIVIDUAL/-------: The software will run for brand new equipment units (i.e. units newly bought and put into use at the beginning of the analysis) for the selected classcode.
2) INDIVIDUAL/INDIVIDUAL: The software will run for the selected equipment unit for the selected classcode.
3) INDIVIDUAL/ALL: The software will run for all existing (e.g. brand new or used) equipment units for the selected classcode.
4) ALL/-------: The software will run for brand new equipment units for all classcodes.
5) ALL/ALL: The software will run for all existing (e.g. brand new or used) equipment units and for all classcodes.

A.3.1.5 Budget

The "Budget" field allows the user (i.e., the Fleet Manager) to specify the maximum amount of money that can be used for the replacement of all the equipment units to be recommended by the ERO Software for the current fiscal year. Enter the desired budget amount and press the "Set" button to specify the budget. The default budget is currently set as 10 million (1.0E+07) dollars.

The budget constraint can be run when both an individual class code and an individual equipment unit are selected, along with a specific amount entered into the budget constraint field (i.e. option 2 in section A.3.1.4), or it can be run with an overall budget amount for “all” equipment units when an individual classcode or all classcodes are selected (i.e. options 3 and 5 respectively in section A.3.1.4). Note that the budget option does not apply to the scenarios where “-------” is selected for the “Equipment Selection” option (i.e. options 1 and 4 in section A.3.1.4).

A.3.1.6 Cost Type

Two different forecasts are made available when SAS is run: “Cost Current Trend” and “Cost Equal Mileage.” Use this to specify which forecast to use.

A.3.1.6.1. Cost Current Trend. This option takes all the information from current TERM data that are “error- and outlier- free” and assumes that the same trend will continue for all future years (Fan et al, 2011a). For example, the current TERM data shows that equipment utilization decreases as equipment gets older and therefore we assume this trend will continue.

A.3.1.6.2. Cost Equal Mileage. This option takes the average annual mileage across all equipment units within the same classcode for the most recent year and uses this value as the expected annual mileage for all equipment ages in that classcode. The annual O&M cost per mileage (or per hour) is calculated for each age for which there is available data and this value is multiplied by the average annual mileage (or hours) to determine the O&M cost for each age. Note that the age of the equipment does not influence the results under this approach and, under this assumption the most recent year’s utilization for the same classcode can change when new data is added at the beginning of each decision year.

A.3.1.7 Benchmark Window

The criteria currently used for replacement within TxDOT include 1) Equipment age, 2) Life usage expressed in miles (or hours), and 3) Life repair costs (adjusted for inflation) relative to original purchase cost (including net adjustment to capital value) (TERM, 2004). Technically speaking, all dynamic programming approaches need to be solved via a rolling horizon for the ERO problem. With that said, the time window must be determined beforehand. If the time window is defined too large, then the cost/mileage forecasting quality will decrease. Conversely, if the rolling horizon time window is small, then the forecasting quality will be really good, but the truncating window effect on the optimization solution quality may become more pronounced. Therefore, a tradeoff between forecasting and optimization exists. In this regard, a 20-year window has been recommended by the PMC members as a consensus, which may impact the cost estimate results and cost comparison to some extent.

A.3.1.7.1. Bench. Year (2/3). If the “Bench. Year (2/3)” radial button is selected, then the benchmark window will be determined by the benchmark solution, which is the age of replacement decided when any 2 of the 3 above criterion are met (e.g. if the age of replacement is 8 years the benchmark will examine a fixed window of 8 years and determine that the equipment unit should be replaced only on year 8 and the software will look no further into the future). If such benchmark window is determined to be "replace" at an age greater than 20, it will be truncated and reset to be replaced only once at the end of the 20-year window (e.g. if the age of replacement is determined to be 25 years then the benchmark will determine that the equipment unit should be replaced only on year 20).

A.3.1.7.2. 20-Year-Fixed. If the "20-Year-Fixed" radial button is selected, the equipment will always be replaced at the end of the 20-year window. When the age of the first replacement is determined, each subsequent replacement will follow at the same age interval until the 20-year window is met (e.g. if the age of replacement is 8 years the benchmark will determine that a brand new equipment unit should be replaced on years 8, 16, and 20). If the benchmark solution is determined to be "replace" at an age greater than 20, it will be truncated and reset to be replaced only once at the end of the 20-year window (e.g. if the age of replacement is determined to be 25 years then the benchmark will determine that the equipment unit should be replaced only on year 20).

A.3.1.8 Editable Data

A.3.1.8.1. Editable. If the "Editable" radial button is selected, the software will use the 6 files (currently located in the folder \TERM Data\Input\EditableData) that can be modified by the user (i.e. Fleet Manager) as the direct input to run optimization. This folder currently includes the following 5 editable Excel data files for each unique 6-digit classcode, "XXXXXX" (1. XXXXXX_Cost_Cur_Trend; 2. XXXXXX_Cost_Cur_Trend_SDP_2Level; 3. XXXXXX_Cost_Cur_Trend_SDP_3Level; 4. XXXXXX_Cost_Equal_Mileage; and 5. XXXXXX_Purchase_Cost).

All the above cost files (excluding the purchase cost file: No. 5) contain forecasted information about the annual mileage, accumulative annual mileage, the annual operating and maintenance (O&M) cost, and the accumulative O&M cost of the selected equipment unit. In particular, if any equipment unit aged greater than 20 years is selected for an optimization run, then the software will use the mileage and operating and maintenance costs of a 20-year-old piece of the same equipment because there is no forecasted data beyond the 20-year window.

Additionally, the first file, XXXXXX_Cost_Cur_Trend, refers to the Deterministic Dynamic Programming (DDP) approach and will be used as the input to the DDP optimization engine when the DDP and Cost Current Trend options are selected. Likewise, the second file, XXXXXX_Cost_Cur_Trend_SDP_2Level, refers to the Stochastic Dynamic Programming (SDP) approach using two vehicle utilization levels (i.e. High/Low mileage) and this file will be used as the input to the SDP optimization engine when the SDP 2-level option is selected. Similarly, the third file, XXXXXX_Cost_Cur_Trend_SDP_3Level, refers to the SDP approach using three vehicle utilization levels (i.e. High/Medium/Low mileage) and will be used as the input to the SDP optimization engine when the SDP 3-level option is selected. The fourth file, XXXXXX_Cost_Equal_Mileage, also refers to the DDP approach and will be used as the input to the DDP optimization engine when the DDP and Cost Equal Mileage options are selected. Finally, the fifth file, XXXXXX_Purchase_Cost, provides the information about the forecasted purchase cost that will be used as input to both DDP and SDP optimization engines.

The user can change the forecasted purchase cost, the annual O&M cost and the annual mileage data in the files, found in the "EditableData" folder, described above as desired in order to run the optimizer for any classcode XXXXXX and any selected equipment units that belong to this classcode.

A sixth file, Raw_XXXXXX_Purchase_Cost_Cur, is also located in this folder, however it is not editable because this file is only used to provide historical purchase cost information.

A.3.1.8.2. SAS. If the "SAS" radial button is selected, SAS code will be called and used to undertake the tasks of raw data reading, cleaning and analyzing, as well as cost estimation and forecasting (as mentioned in section A.1.2), and to generate the necessary 6 files as mentioned above on the fly, five of which are used as the input into the DP optimization engine. These files can be viewed for any classcode in the output folder (currently located in folder \TERM Data\Output) as mentioned in section A.3.1.2 and can be copied and pasted to the "EditableData" folder as mentioned in section A.3.1.8.1 if desired.

A.3.1.9 Run

If the "Run" button is selected the software will execute the optimization engine according to the user specifications. Before running the program, the user must specify where the SAS executable file is located by clicking "File" and selecting "Options" from the dropdown menu, as will be described in section A.3.3. To run the program, there are further options available and they can be found by selecting the "Options" tab as discussed in the following section.

A.3.2 OPTIONS

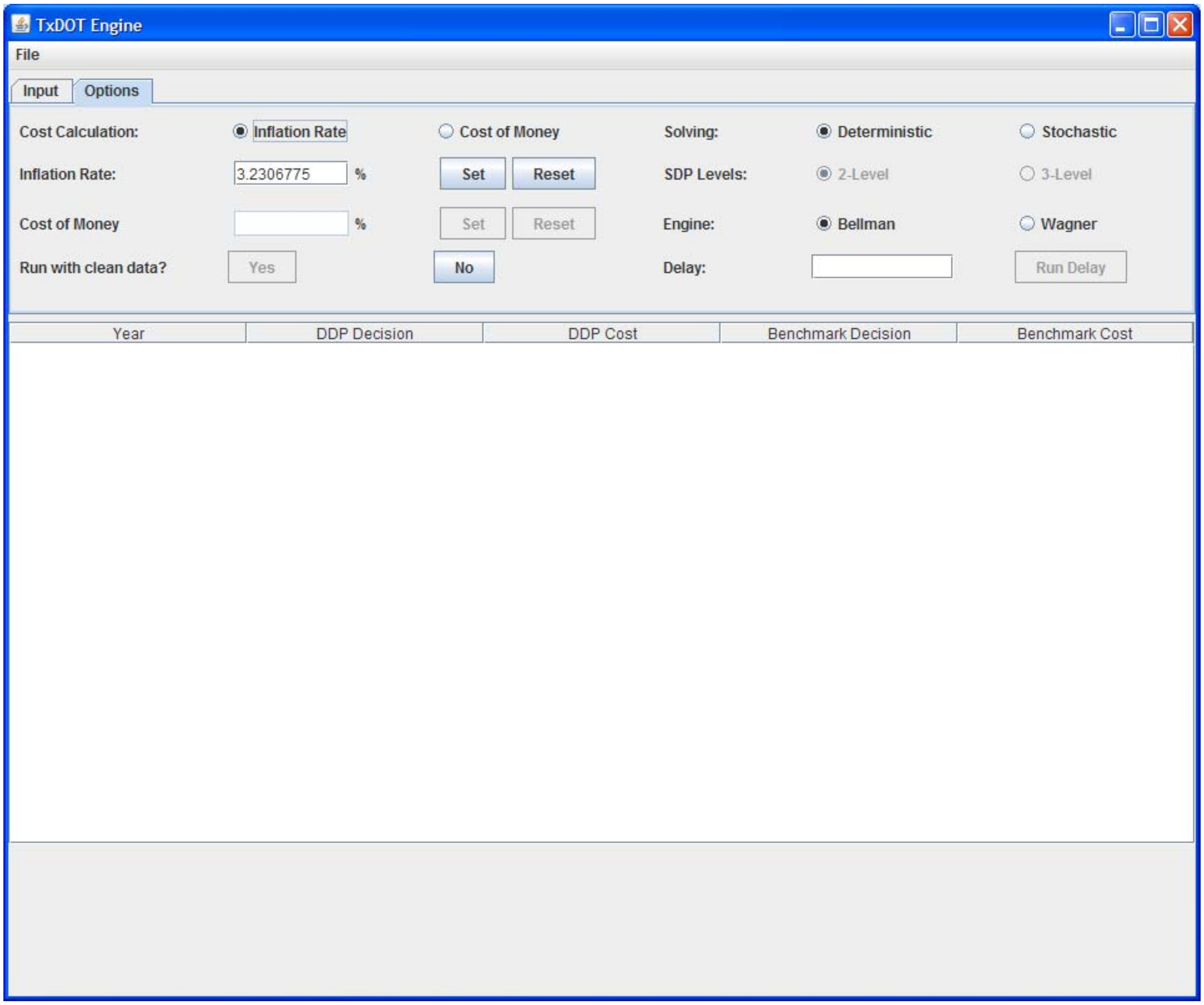


Figure A.0.8: Standard Interface – Show Options

To view the Options Interface click the "Options" Tab at the top of the screen next to the Input tab. Click the "Input" Tab to return to the Input Interface as desired. Clicking the "Options" Tab will bring up a screen similar to the one shown in Figure A.3.2, which allows the user to specify more parameters that the program will need to use. These buttons and fields are discussed in detail below.

A.3.2.1 Cost Calculation

The Cost Calculation specifies whether to use "Inflation Rate" or "Cost of Money" to run the optimization. Only one option may be selected at a time; if the "Inflation Rate" radial button is selected then the "Cost of Money" field is disabled, or if the "Cost of Money" radial button is selected then the "Inflation Rate" field is disabled.

A.3.2.3 Inflation Rate

The inflation rate is typically defined as the percentage rate of change in price level over time. The default value is currently set at 3.2306775% and will not change over time; consequently users may wish to reset this field with a more accurate value based on the future economy or their particular needs.

A.3.2.2.1. Set. First enter a value (as a percentage) into the "Inflation Rate" field. By clicking the "Set" button the inflation rate is set to the value that was entered until the program is closed.

A.3.2.2.2. Reset. By clicking the "Reset" button the inflation rate is set back to a default value of 3.2306775%. This rate is calculated based on the Consumer Price Index (CPI) inflation rate (Bureau of Labor Statistics, 2009) as mentioned in the technical report.

A.3.2.4 Cost of Money

Cost of money is typically defined as the interest that could be earned if the amount invested in one area of business is instead invested in another. By selecting this option it is assumed that TxDOT wishes to evaluate whether it is more cost effective to invest in equipment replacement or to invest in areas other than equipment replacement and show the comparative benefits of such decisions. The addition of this option, which allows for the user to utilize an interest rate that equals the cost of money instead of the inflation rate, was due to a suggestion by TxDOT.

A.3.2.3.1.Set. First enter a value (as a percentage) into the "Cost of Money" field. By clicking the "Set" button the cost of money is set to the value that was entered until the program is closed.

A.3.2.3.2. Reset. By clicking the "Reset" button the cost of money is set to a default of 0.0.

A.3.2.5 Run with clean data?

The "Run with clean data" option specifies whether or not to clean the data before running the software. Running the engine without removing both the data errors and outliers would cause problems with the software and the results would not be beneficial to the user. However, this option exists in order for the user to see the uncleaned intermediate tables in the Output Directory, as mentioned in section A.3.1.2.

A.3.2.4.1. Yes. The optimization engine must be run with clean data, hence the "Yes" button will default to be inactive (i.e. unless the "No" option is selected the "Yes" option will always be selected).

A.3.2.4.2. No. By selecting the "No" button, the optimization engine will not be run but the SAS macro, without cleaning the data and removing the data outliers, is still called and users will be able to view and examine the intermediate files generated by SAS for informational purposes. A message will be displayed through a pop-up window informing the user to browse to the "Output Directory" to see the data.

A.3.2.6 Solving

Both DDP and SDP approaches have been applied and implemented to solve the ERO problem based upon different assumptions. Specifically, the DDP approach assumes that the equipment utilization is predetermined, although it may still depend upon its equipment age. However, for the SDP approach, the uncertainty involved in equipment utilization at each year is taken into account. In other words, the utilization may not be pre-determined (i.e., fixed) but actually random and depends upon operating environment, because it is expected that different usage patterns may lead to different optimal solutions (Fan et al, 2011b and 2011c).

A.3.2.5.1. Deterministic. If the "Deterministic" radial button is selected, the optimization will use the DDP approach, while the SDP Level options will be grayed out and disabled.

A.3.2.5.2. Stochastic. If the "Stochastic" radial button is selected the optimization will use the SDP approach; the "Cost Equal Mileage" option, as mentioned in A.3.1.6, will be grayed out and become inactive. When this button is selected there will be two options available; SDP 2-Level and SDP 3-Level, as will be described in section A.3.2.6.

A.3.2.7 SDP Level

Once the "Stochastic" radial button is selected, the two SDP Level options become available.

A.3.2.6.1. SDP 2-Level. If the "SDP – 2Level" radial button is selected the file XXXXXX_Cost_Cur_Trend_SDP_2Level can be either obtained from the "EditableData" folder described in section A.3.1.8.1 or generated by the SAS macro on the fly as described in section A.3.1.8.2, with both referring to two vehicle utilization levels (i.e. High/Low mileage), and this will be used as the input to the DP optimization engine.

A.3.2.6.2. SDP 3-Level. If the "SDP – 3Level" radial button is selected the file XXXXXX_Cost_Cur_Trend_SDP_3Level can be either obtained from the "EditableData" folder described in section A.3.1.8.1 or generated by the SAS macro on the fly as described in section A.3.1.8.2, with both referring to three vehicle utilization levels (i.e. High/Medium/Low mileage), and this will be used as the input to the DP optimization engine.

A.3.2.8 Engine

The ERO will make a decision on whether to replace or retain at each stage (typically annually) and it can be solved using two typical dynamic programming approaches; these are the Bellman and Wagner formulations (Fan et al, 2011b). As of now, the Bellman method is slightly faster because the data preprocessing necessary for the Wagner formulation is not needed, but both methods provide the same results.

A.3.2.7.1. Bellman. If the "Bellman" radial button is selected, the Bellman approach will be used to run optimization. Detailed information about the Bellman approach can be found in the technical report.

A.3.2.7.2. Wagner. If the "Wagner" radial button is selected, the Wagner approach will be used to run optimization. Detailed information about the Wagner approach can be found in the technical report.

A.3.2.9 Delay

The "Delay" field specifies how many years to delay the decision to replace based on the optimized solution. If a value of 0 is entered then the engine will ignore the first replacement. If a value greater than 0 is entered then the engine will delay the first replacement for the *value* number of years. If a negative value is entered, then the engine will replace the equipment by the *absolute value* number of years earlier than the optimized solution. The "Delay" option is only available when the "INDIVIDUAL/-------" or "INDIVIDUAL/INDIVIDUAL" options are selected, and the delay logic will not be available for the other three options (i.e., "INDIVIDUAL/ALL", "ALL/-------", and "ALL/ALL") as mentioned in section A.3.1.4.

Also, the value entered in the "Delay" field should not cause the age of the vehicle to be negative or to exceed 20 years. Otherwise an error message will be displayed.

Additionally, the user can only enter the desired delay time and run the delay logic after a primary optimization run is complete. The GUI will display the results for the delay setting specified by the user one at a time, and the results can be exported, saved and viewed in the corresponding Excel file. In addition, the software will run an evaluation of cost increases corresponding to the specific delay time (either positive or negative delays, as long as they are feasible, as mentioned above) against the optimal replacement solutions. Furthermore, as suggested by the TxDOT PMC members, the software can automatically get such evaluation results for *all* feasible delay times (i.e., TxDOT current benchmark replacement year plus or minus 3) against the optimal replacement solution recommended by the dynamic programming approach after each optimization run, and then automatically save the results in the Output Directory, as described in section A.3.1.2. These results are further explained in section A.4.2.

A.3.3 SAS INSTALLATION LOCATION OPTION

To access the "SAS Installation Location Options" window so the user can specify the SAS executable file location, as mentioned in section A.3.1.9, click the File drop-down menu, located at the top of the screen, as can be seen in Figures A.3.1 and A.3.2 and click "Options." A screen similar to Figure A.3.3 should be displayed.

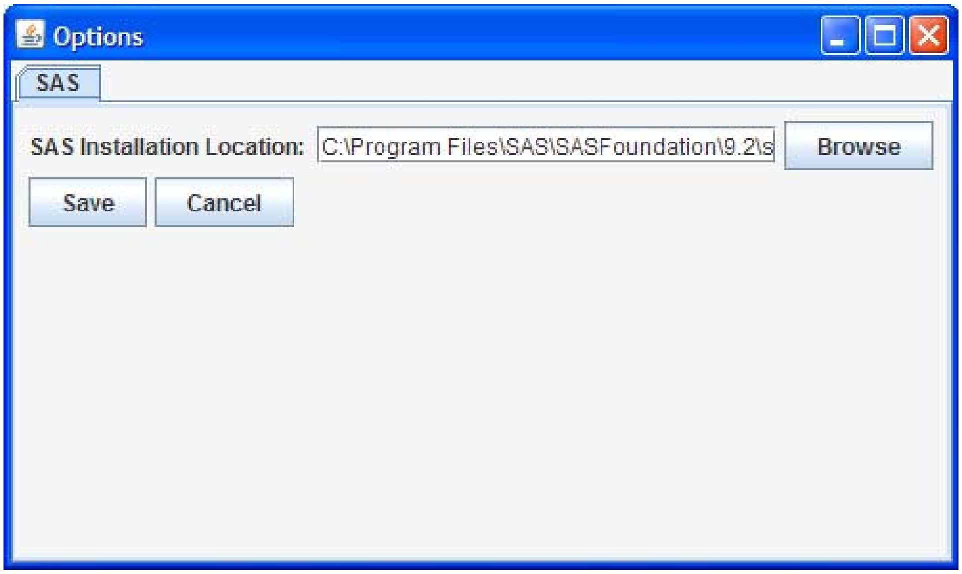


Figure A.0.9: Options Screen

Browse to where the SAS executable is found, select, and click “Open” (Note that the default location is C:\Program Files\SAS\SASFoundation\9.2\sas.exe, which is also the default location at the time the SAS software was installed). Click “Save” and then close the window.

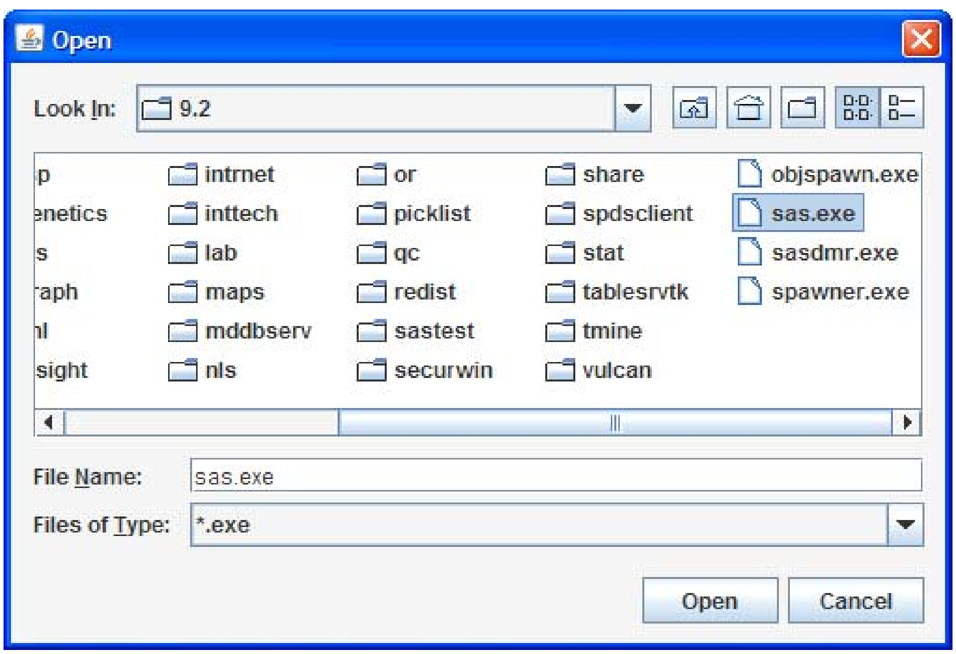


Figure A.0.10: Open sas.exe

A.3.4 OPTIMIZATION RUNS

To conduct an optimization run, the user should follow the subsequent procedures:

- First, follow the steps described in section A.3.3 to select the SAS executable file.
- Next, use the “Input” tab to select the Input and Output directories.
- Enter the desired Budget amount.

- Choose the appropriate Cost Type, Benchmark Window and Editable data selections to fit the desired user specifications.
- Choose the combination of Class Code and Equipment Selection desired, as described in sections A.3.1.3 and A.3.1.4.
- Click the "Options" tab.
- Select the appropriate Cost Calculation, Inflation Rate or Cost of Money, as described in sections A.3.2.1 through A.3.2.3.
- Enter the desired value into either the Inflation Rate field or the Cost of Money field.
- Choose which optimization engine to run: Bellman or Wagner.
- Choose which dynamic programming approach to use: Stochastic or Deterministic.
- If Stochastic is chosen, choose either SDP 2-Level or SDP 3-level.
- Finally, click and navigate back to the "Input" tab again, then click the **Run** button.
- Only after the optimization run is complete, the user can enter any feasible delay time, as desired, and run the delay logic, as mentioned in section A.3.2.8.

Figure A.3.5 shows an example of the ERO with a default budget and Inflation Rate selected, as well as Cost Current Trend, 20-Year-Fixed Benchmark Window, SAS Data option, all ClassCodes, no Equipment Selection, no Delay, the SDP 2-Level approach and Bellman approach selected.

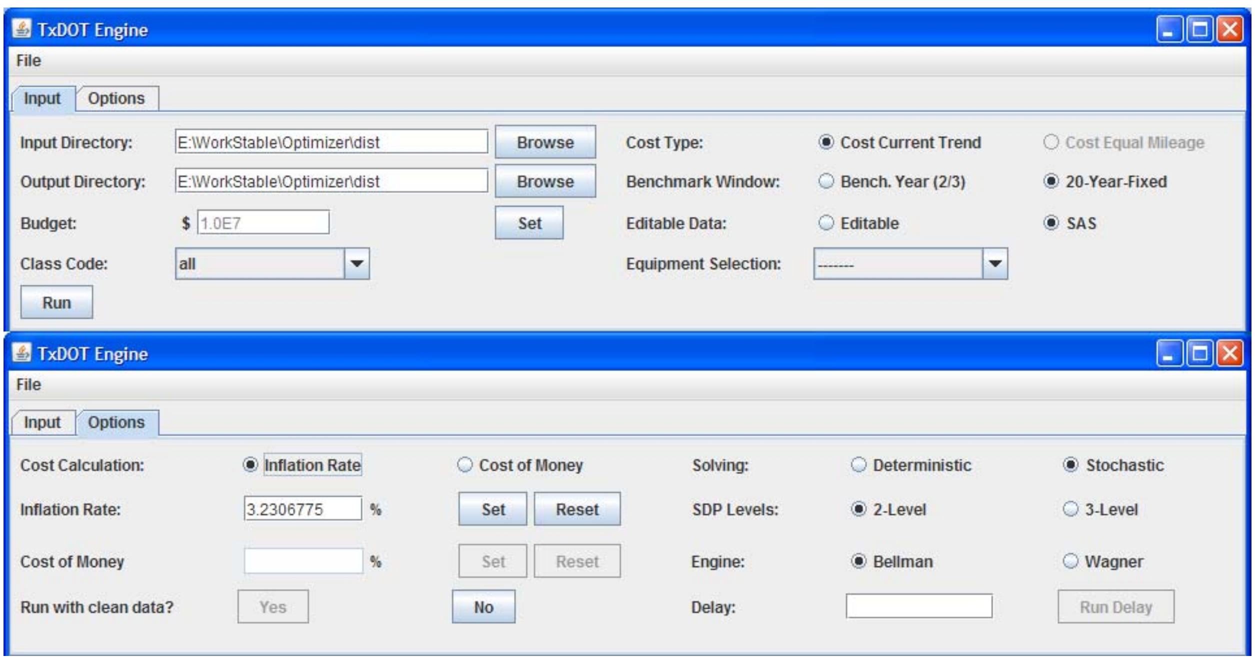


Figure A.0.11: Cropped ERO Input and Options Screens

A SAS dialog box, similar to Figure A.3.6, will appear indicating that SAS is running. After SAS has finished running the results will be displayed through the Graphic User Interface (GUI) and can be exported, saved and viewed as Excel files as will be mentioned in section A.4.1. The presentation of the results will be further discussed in detail in Chapter A.4.

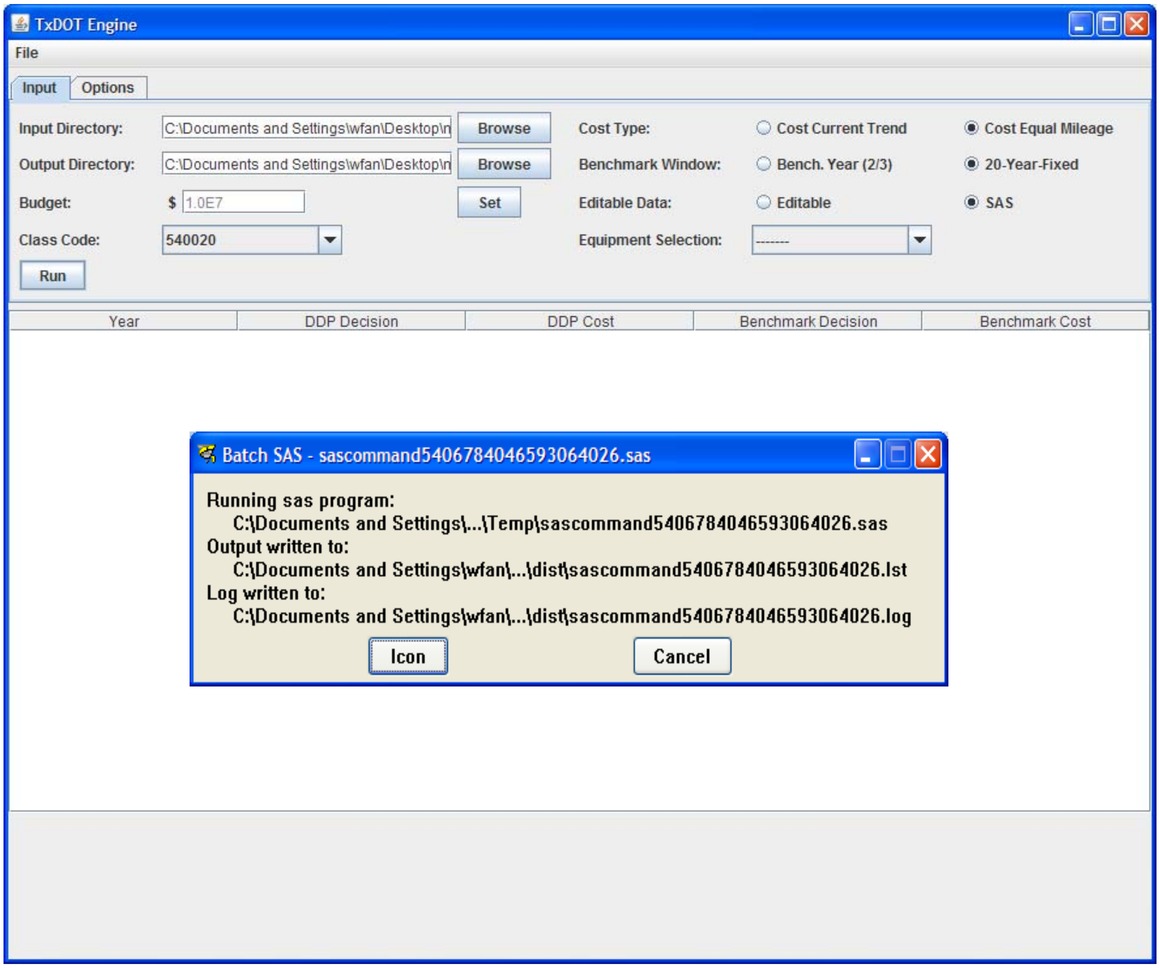


Figure A.0.12: SAS Dialog Box

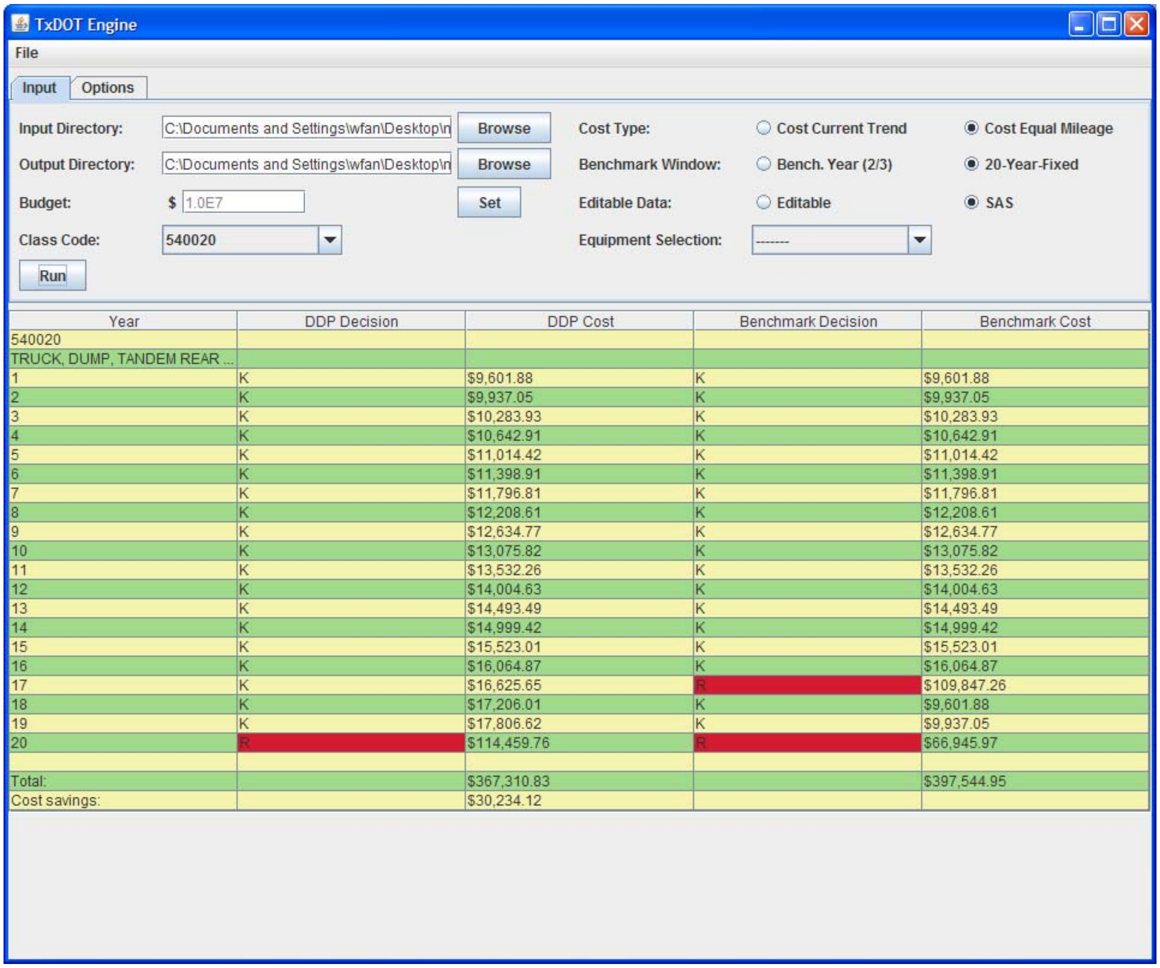
CHAPTER A.4: RESULTS PRESENTATION

As mentioned in Chapter A.1, the developed ERO solution methodology in this project is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles, both with and 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 (as will be discussed in section A.4.1); 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 (as will be discussed in section A.4.2).

A.4.1 DP OPTIMIZATION RESULTS WITHOUT BUDGET CONSIDERATION

A.4.1.1 DP GUI Results

Once optimization has been run, the results will be displayed through the GUI, as shown in Figure A.4.1. The second and fourth columns refer to the (K)eep or (R)eplace decision at the beginning of that year as shown in the same row. The decision to replace is further indicated by cells colored red. At the bottom of the table a “Total” row will be calculated, showing the totals for both the optimized solution and the benchmark solution. The last row will be the “Cost savings” row which calculates an estimate of how much money will be saved over the displayed time window using the optimized solution.



Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost
540020				
TRUCK, DUMP, TANDEM REAR ...				
1	K	$9,601.88	K	$9,601.88
2	K	$9,937.05	K	$9,937.05
3	K	$10,283.93	K	$10,283.93
4	K	$10,642.91	K	$10,642.91
5	K	$11,014.42	K	$11,014.42
6	K	$11,398.91	K	$11,398.91
7	K	$11,796.81	K	$11,796.81
8	K	$12,208.61	K	$12,208.61
9	K	$12,634.77	K	$12,634.77
10	K	$13,075.82	K	$13,075.82
11	K	$13,532.26	K	$13,532.26
12	K	$14,004.63	K	$14,004.63
13	K	$14,493.49	K	$14,493.49
14	K	$14,999.42	K	$14,999.42
15	K	$15,523.01	K	$15,523.01
16	K	$16,064.87	K	$16,064.87
17	K	$16,625.65	R	$109,847.26
18	K	$17,206.01	K	$9,601.88
19	K	$17,806.62	K	$9,937.05
20	R	$114,459.76	R	$66,945.97
Total:		$367,310.83		$397,544.95
Cost savings:		$30,234.12		

Figure A.0.13: DDP Results in GUI

A.4.1.2 Exporting DP Results

The GUI table shown in Figure A.4.1 can be exported to a CSV file, which can be opened in Excel, by selecting the “File” drop down menu then “Export As CSV” and save it to any location desired. This location does not become default after the first save; the user is required to perform this step after each run to save and export the excel results. After saving, double click the CSV file created to display the results in Excel. In the event that Excel does not open automatically, open Excel first and then load the CSV file.

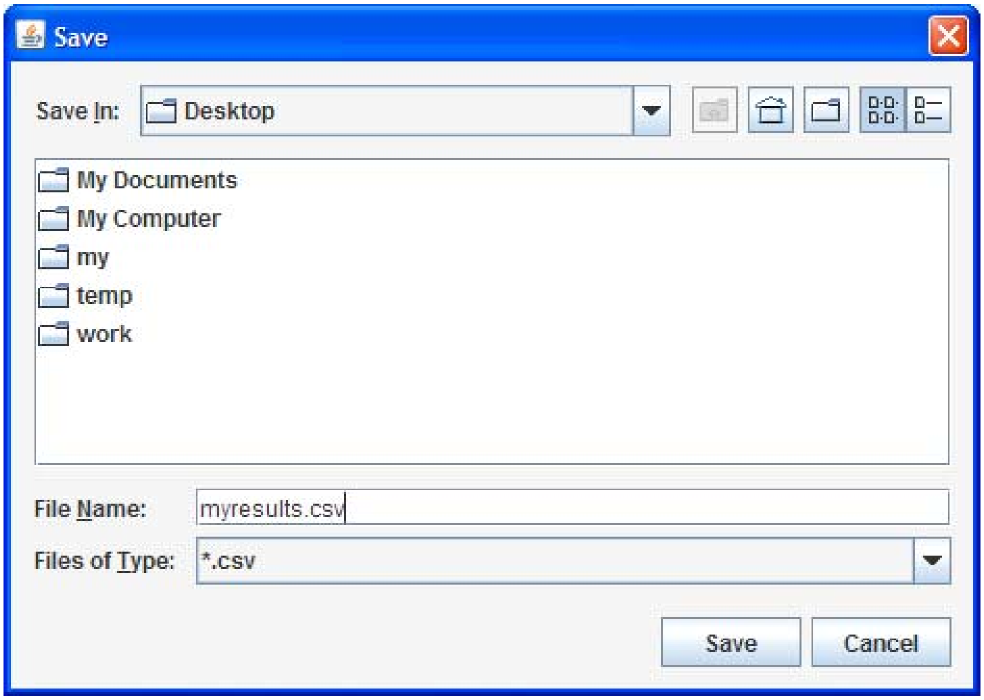
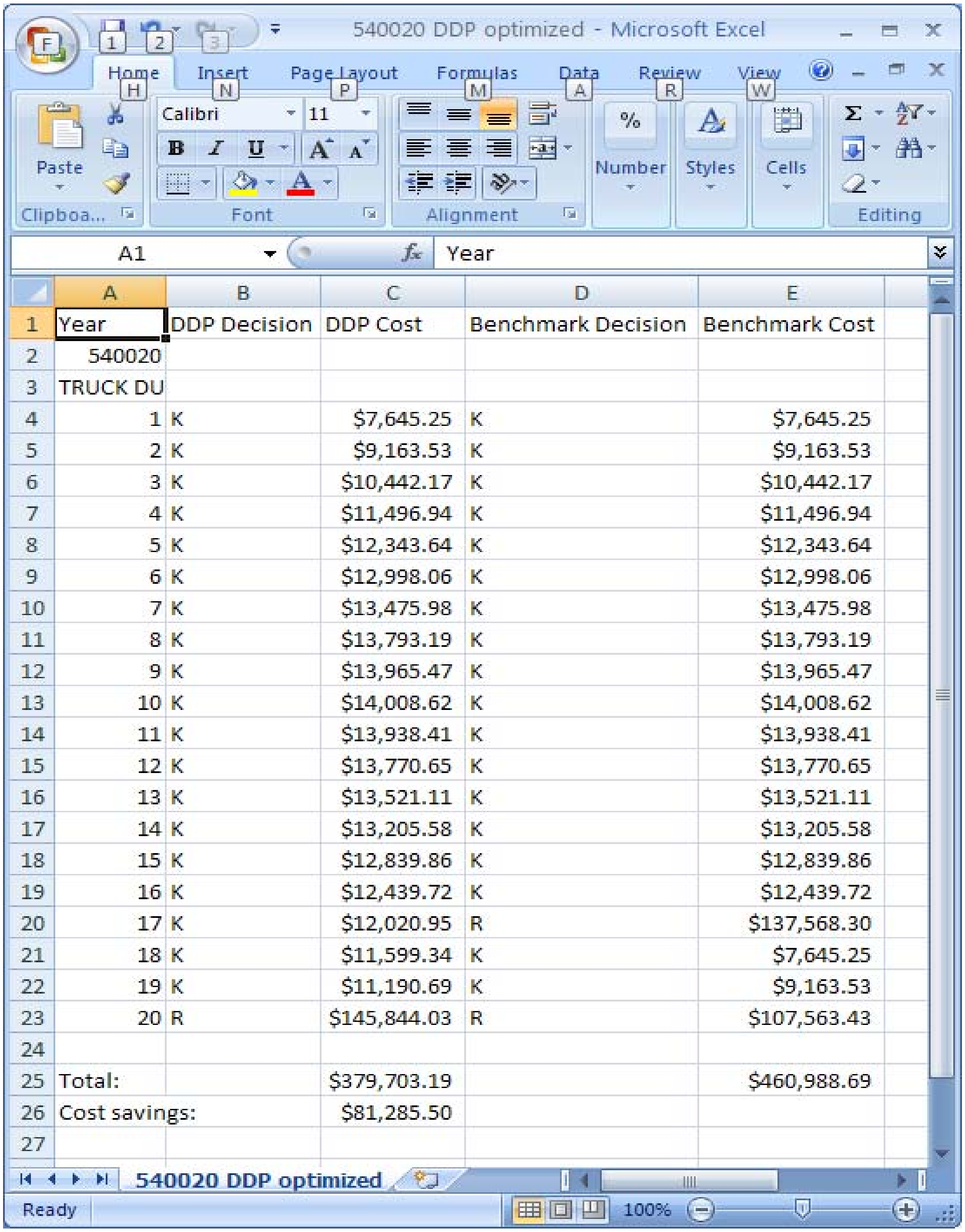


Figure A.0.14: Save As CSV

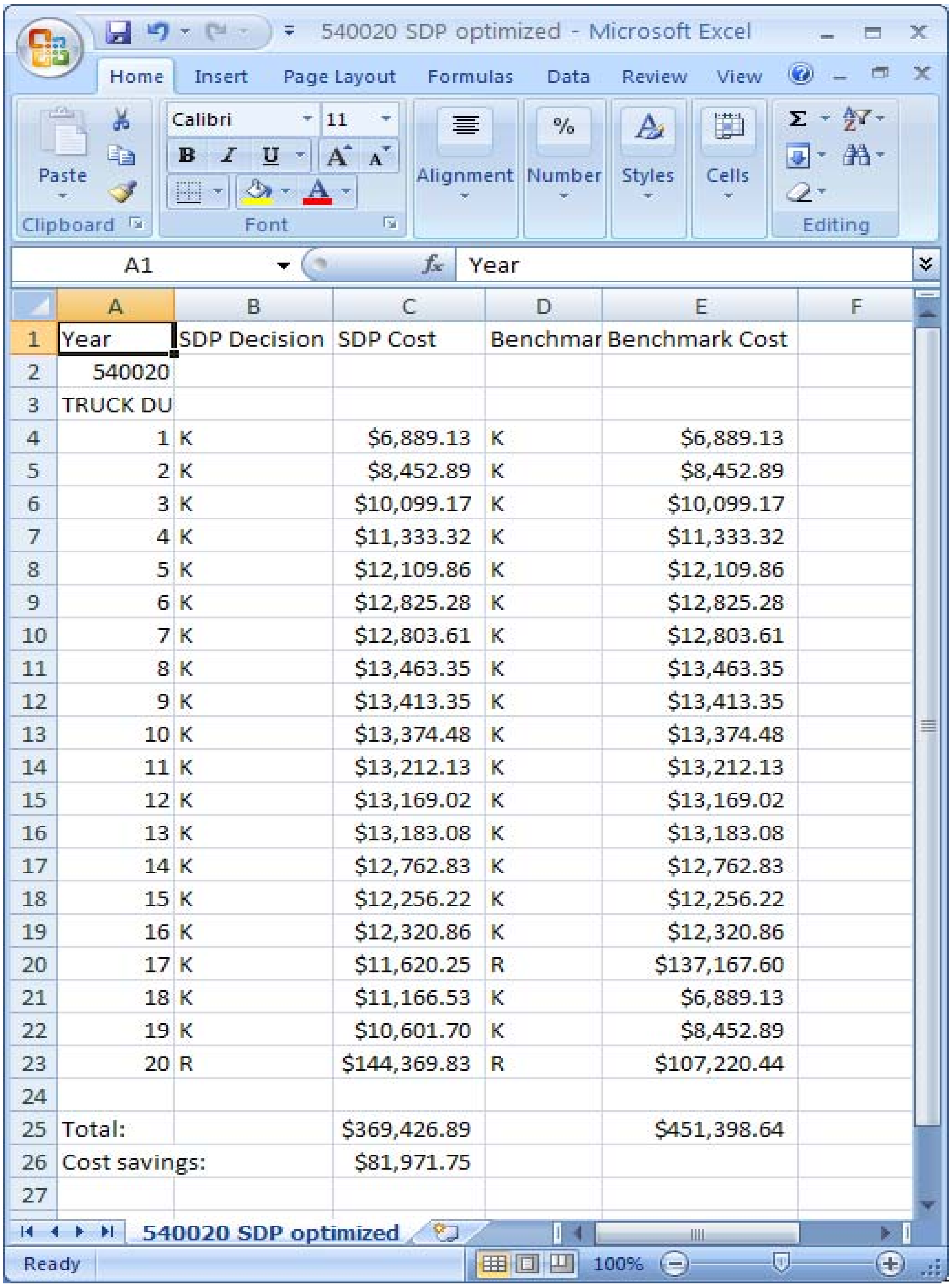
When opened in Excel, the results will look similar to Figures A.4.3 (for DDP results) and A.4.4 (for SDP results). Note that the first column is the number of years into the future, starting from the beginning of the current fiscal year (i.e. the decision year). The second column refers to the optimized (K)eep or (R)eplace decision at the beginning of the year shown in the same row. The third column represents the cost associated with the optimized decision, as shown in that row. The fourth column has the same meaning as the second column but corresponds to the cost related to the TxDOT benchmark rules. The last (fifth) column shows the cost information associated with the fourth column of the benchmark decision. If the decision is to Keep for a particular year then the associated cost refers to the annual operating and maintenance cost (adjusted for inflation). However if the decision is to Replace for a particular year then the associated cost represents the purchase cost of a new equipment unit at the beginning of the year; plus the annual operating and maintenance cost; minus the salvage value of the old equipment unit at the end of the year (all adjusted for inflation). In the example, Figure A.4.3, the DDP approach saves a total estimated cost of $81,285.50 over the 20-year window when compared against the current benchmark rules used by TxDOT.



	A	B	C	D	E
1	Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost
2	540020				
3	TRUCK DU				
4	1	K	$7,645.25	K	$7,645.25
5	2	K	$9,163.53	K	$9,163.53
6	3	K	$10,442.17	K	$10,442.17
7	4	K	$11,496.94	K	$11,496.94
8	5	K	$12,343.64	K	$12,343.64
9	6	K	$12,998.06	K	$12,998.06
10	7	K	$13,475.98	K	$13,475.98
11	8	K	$13,793.19	K	$13,793.19
12	9	K	$13,965.47	K	$13,965.47
13	10	K	$14,008.62	K	$14,008.62
14	11	K	$13,938.41	K	$13,938.41
15	12	K	$13,770.65	K	$13,770.65
16	13	K	$13,521.11	K	$13,521.11
17	14	K	$13,205.58	K	$13,205.58
18	15	K	$12,839.86	K	$12,839.86
19	16	K	$12,439.72	K	$12,439.72
20	17	K	$12,020.95	R	$137,568.30
21	18	K	$11,599.34	K	$7,645.25
22	19	K	$11,190.69	K	$9,163.53
23	20	R	$145,844.03	R	$107,563.43
24					
25	Total:		$379,703.19		$460,988.69
26	Cost savings:		$81,285.50		
27					

Figure A.0.15: DDP Results in Excel

Similarly, Figure A.4.4 follows the same format as Figure A.4.3. However, it represents the results for the SDP approach. The cost associated with the decision to either Keep or Replace is calculated in the same manner as that in the DDP approach. In the example, Figure A.4.4, the SDP approach saves a total estimated cost of $81,971.75 over the 20-year window when compared against the current benchmark rules used by TxDOT. In these two examples the cost to replace the equipment unit belonging to this classcode (540020) on the 20th year is slightly different between the optimized DDP/SDP decision and the Benchmark decision. This is because in both cases the optimal decision is to keep the equipment unit for all 20 years and replace on year 20, and the benchmark decision was to replace at years 17 and 20. Therefore, when the equipment unit is replaced on year 20, the optimal decision requires the salvage of a 20-year-old piece of equipment instead of the 3-year-old piece of equipment decided by the benchmark solution. As can be seen, the newer equipment unit has a higher salvage value, which reduces the overall cost of replacement on the 20th year.



	A	B	C	D	E	F
1	Year	SDP Decision	SDP Cost	Benchmar	Benchmark Cost	
2	540020					
3	TRUCK DU					
4	1	K	$6,889.13	K	$6,889.13	
5	2	K	$8,452.89	K	$8,452.89	
6	3	K	$10,099.17	K	$10,099.17	
7	4	K	$11,333.32	K	$11,333.32	
8	5	K	$12,109.86	K	$12,109.86	
9	6	K	$12,825.28	K	$12,825.28	
10	7	K	$12,803.61	K	$12,803.61	
11	8	K	$13,463.35	K	$13,463.35	
12	9	K	$13,413.35	K	$13,413.35	
13	10	K	$13,374.48	K	$13,374.48	
14	11	K	$13,212.13	K	$13,212.13	
15	12	K	$13,169.02	K	$13,169.02	
16	13	K	$13,183.08	K	$13,183.08	
17	14	K	$12,762.83	K	$12,762.83	
18	15	K	$12,256.22	K	$12,256.22	
19	16	K	$12,320.86	K	$12,320.86	
20	17	K	$11,620.25	R	$137,167.60	
21	18	K	$11,166.53	K	$6,889.13	
22	19	K	$10,601.70	K	$8,452.89	
23	20	R	$144,369.83	R	$107,220.44	
24						
25	Total:		$369,426.89		$451,398.64	
26	Cost savings:		$81,971.75			
27						

Figure A.0.16: SDP Results in Excel

A.4.2 OPTIMIZATION RESULTS WITH BUDGET CONSIDERATION

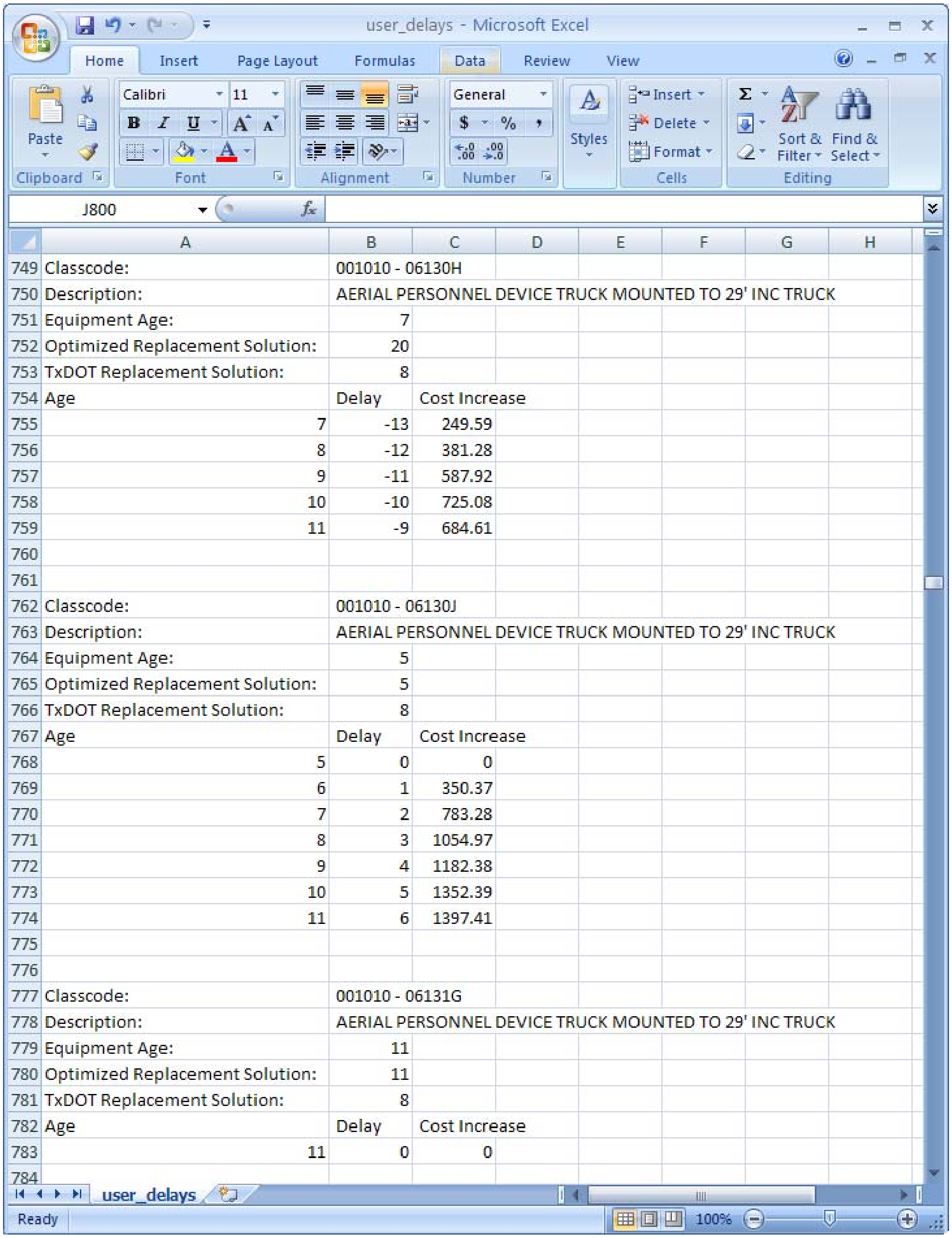
As the software runs, user delay files are automatically created and stored in the Output Directory (currently located in folder \TERM Data\Output), as described in section A.3.1.2. These files are "user_delays.csv; user_delay_increase.csv"; "Delay.csv"; and "Replacement_Final_Recomendation.csv". As mentioned in section A.3.2.8, after each optimization run, the software will automatically evaluate delay results for *all* feasible delay times (i.e., TxDOT current benchmark replacement year plus or minus 3 and less than 20 years) against the optimal replacement solution recommended by the DP approach and save the results as these first three files in the Output Directory.

Note that, even though the term "Delay" is found in the titles of these output files, they are generated every time the DP optimization is run whether or not any Delay time is specified. Also, the first and second files, "user_delays.csv" and "user_delay_increase.csv", respectively, are outputs of the first round DP optimization and are used only for informational purposes for the user to review the increase in cost, compared to the optimized decision, as the delay changes. The third file, "Delay.csv", is the output of first round dynamic programming (DP) optimization and it will be used as the input into the second round knapsack programming optimization. The fourth file, "Replacement_Final_Recomendation.csv", which is the output of the second round knapsack programming optimization, contains the optimal equipment replacement results intended to maximize the benefits for the user given the specified annual budget for the decision year. It is emphasized that the "Delay.csv" file provides the input to the second round of knapsack programming which produces the "Replacement_Final_Recomendation.csv" file containing the final output of the ERO Optimization with budget constraints considered.

The following sections describe the layout of these four files. The settings used to create the examples below were: default budget and default Inflation Rate selected, Cost Current Trend, 20-Year-Fixed Benchmark Window, SAS Data option, ClassCode "001010", all Equipment Selection, no Delay, and the SDP 2-Level approach and the Bellman approach selected.

A.4.2.1 User_Delays.csv

This file is generated to show the user (i.e., Fleet Manager) the impact of the delay on the increase in cost as compared to the optimized replacement age. It shows the classcode and equipment unit combinations that were run, as well as a description of that specific unit, its current equipment age, and the corresponding Optimized Replacement Solution and TxDOT Replacement Solution (i.e. Benchmark Solution). Additionally, an Age/Delay/Cost Increase table is provided for each ClassCode/Equipment Selection combination that was run. This table provides information about how much the cost increases compared to the optimized decision as the delay changes. This allows the user to determine the estimated total increase in cost of delaying the replacement of that particular piece of equipment. The Age column pertains to the age of the actual replacement unit; the Delay column represents the number of years differing between the actual replacement and the optimization recommendation for the Age shown in that row; and the Cost Increase column reflects the additional cost incurred compared to the total cost of the optimized decision for the Age shown in that row. For example, in Figure A.4.6, if Equipment Unit "001010 - 06130H" is replaced 10 years earlier than the optimized replacement (i.e. Delay = -10) then that decision will cause a total cost increase of $725.08 and its age at the time of replacement will be 10 as compared to the optimized replacement age of 20. Also, if replacement of Classcode “001010” Equipment Unit “06130J” is delayed by two years (i.e. Delay = 2) then that decision will cause a total cost increase of $783.28 and its age at the time of replacement will be 7, as compared to the optimized replacement age of 5.

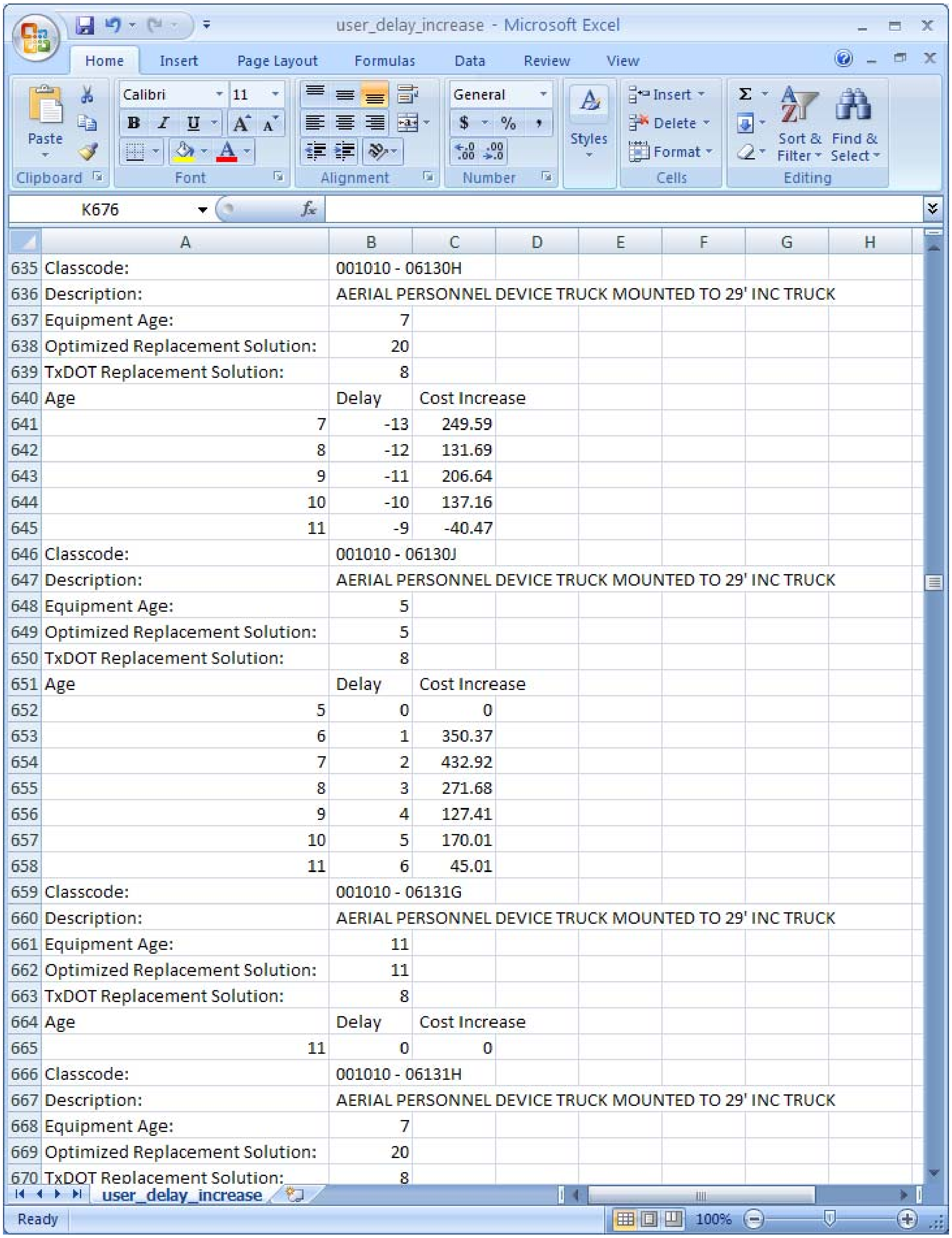


	A	B	C
749	Classcode:	001010 - 06130H	
750	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
751	Equipment Age:	7	
752	Optimized Replacement Solution:	20	
753	TxDOT Replacement Solution:	8	
754	Age	Delay	Cost Increase
755	7	-13	249.59
756	8	-12	381.28
757	9	-11	587.92
758	10	-10	725.08
759	11	-9	684.61
760			
761			
762	Classcode:	001010 - 06130J	
763	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
764	Equipment Age:	5	
765	Optimized Replacement Solution:	5	
766	TxDOT Replacement Solution:	8	
767	Age	Delay	Cost Increase
768	5	0	0
769	6	1	350.37
770	7	2	783.28
771	8	3	1054.97
772	9	4	1182.38
773	10	5	1352.39
774	11	6	1397.41
775			
776			
777	Classcode:	001010 - 06131G	
778	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
779	Equipment Age:	11	
780	Optimized Replacement Solution:	11	
781	TxDOT Replacement Solution:	8	
782	Age	Delay	Cost Increase
783	11	0	0
784			

Figure A.0.17: User_Delays.csv

A.4.2.2 User_Delay_Increase.csv

This file is very similar to the "User_Delay.csv" file in that it shows the classcode and equipment unit combinations that were run, as well as a description of that unit, its current equipment age, and the corresponding Optimized Replacement Solution and TxDOT Replacement Solution (i.e. Benchmark Solution). Again, an Age/Delay/Cost Increase table is provided for each ClassCode/Equipment Selection combination that was run. The first row of each table shows the additional increase in cost if the replacement occurs at the current age compared to the optimized decision. For the rest of the table, the delay is increased by another year and the cost increase is displayed compared to the previous year's cost, as opposed to a comparison with the optimized decision. This allows the user to review the cost increase resulting from the delay of an additional year. For example, in Figure A.4.7, if Equipment Unit "001010 – 06130H" is replaced 10 years earlier than the optimized decision (i.e. Delay = -10), then that decision will cause an additional cost increase of $137.16 compared to the decision of replacement 11 years earlier (i.e. Delay = -11). As mentioned above, the total cost increase of replacing 10 years early is equal to $725.08. This value is equal to the cost increase of Delay = -13 plus Delay = -12 plus Delay = -11 plus Delay = - 10, as found in Figure A.4.6, or $249.59 + $131.69 + $206.64 + $137.16 = $725.08.



	A	B	C
635	Classcode:	001010 - 06130H	
636	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
637	Equipment Age:	7	
638	Optimized Replacement Solution:	20	
639	TxDOT Replacement Solution:	8	
640	Age	Delay	Cost Increase
641	7	-13	249.59
642	8	-12	131.69
643	9	-11	206.64
644	10	-10	137.16
645	11	-9	-40.47
646	Classcode:	001010 - 06130J	
647	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
648	Equipment Age:	5	
649	Optimized Replacement Solution:	5	
650	TxDOT Replacement Solution:	8	
651	Age	Delay	Cost Increase
652	5	0	0
653	6	1	350.37
654	7	2	432.92
655	8	3	271.68
656	9	4	127.41
657	10	5	170.01
658	11	6	45.01
659	Classcode:	001010 - 06131G	
660	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
661	Equipment Age:	11	
662	Optimized Replacement Solution:	11	
663	TxDOT Replacement Solution:	8	
664	Age	Delay	Cost Increase
665	11	0	0
666	Classcode:	001010 - 06131H	
667	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED TO 29' INC TRUCK	
668	Equipment Age:	7	
669	Optimized Replacement Solution:	20	
670	TxDOT Replacement Solution:	8	

Figure A.0.18: User_Delay_Increase.csv

A.4.2.3 Delay.csv

As mentioned earlier, this file is used as the direct input into the second round of knapsack programming optimization and each column is explained below.

CLASSCODE – lists the classcode(s) which have been run and are being described in each row.

EQUIPMENT_CODE – gives the code of the specific equipment unit being described in each row.

EQUIPMENT_AGE – gives the current age of the specific equipment unit in each row.

DELAYED_REPLACEMENT_AGE – represents the actual replacement age after delay.

INCREASE_IN_COST – denotes the additional cost incurred for this particular DELAYED_REPLACEMENT_AGE (i.e. the actual replacement age) as compared to the total cost of the optimized decision.

COST_SAVINGS – shows the cost saved by this particular DELAYED_REPLACEMENT_AGE (i.e. the actual replacement age) as compared to the total cost of the benchmark decision.

CLASSCODE_PURCHASE_COST – gives the current forecasted purchase cost for a brand-new equipment unit belonging to the classcode being described in each row.

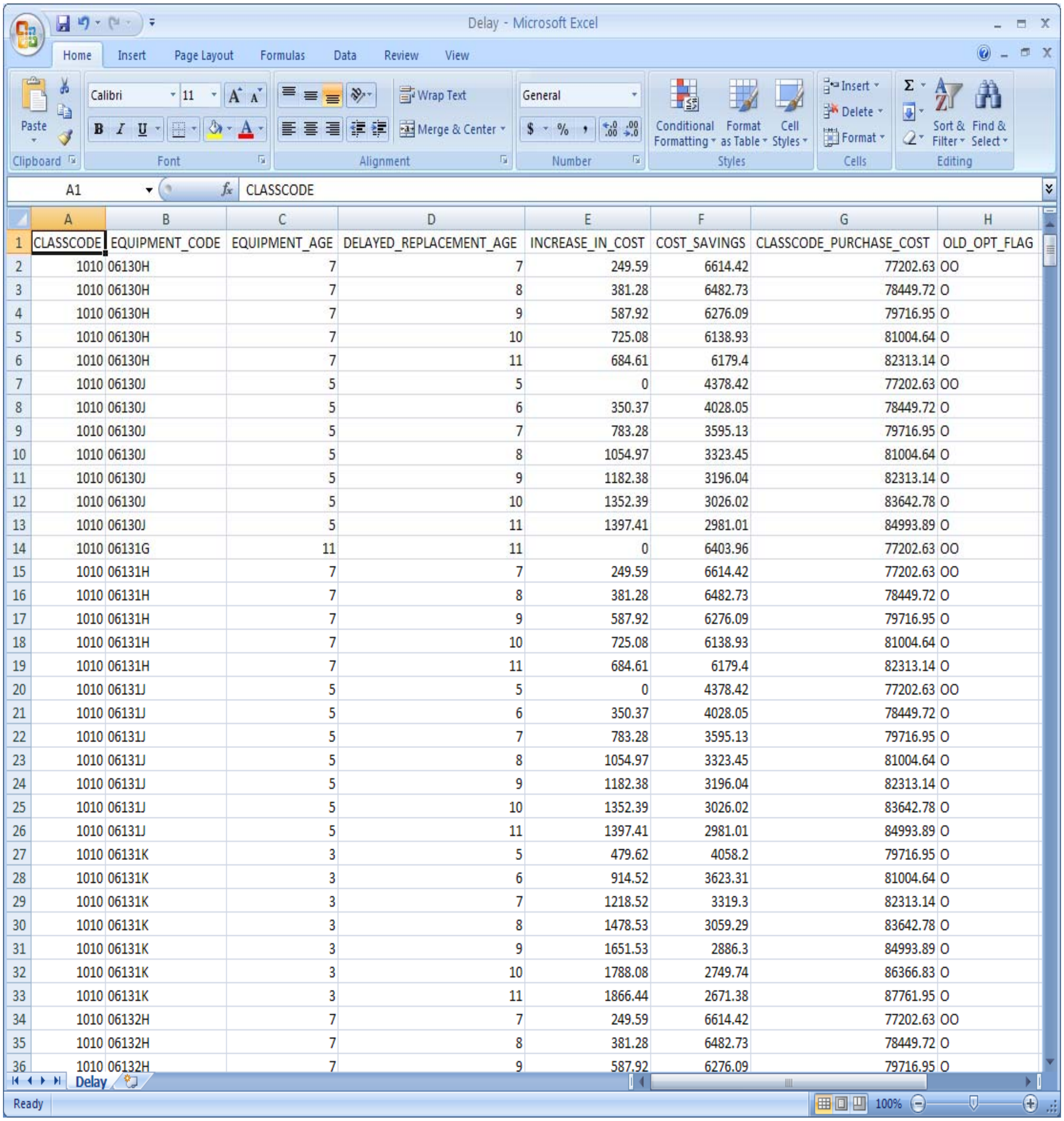
OLD_OPT_FLAG – Gives a lettered code for each equipment unit in each row as defined below:

MM – Too old, greater than or equal to 3 years plus the optimized age of replacement.

MMM – Too old, greater than or equal to 20 years.

OO – Represents a candidate for immediate replacement of equipment units at the current year.

M or O – Denotes a candidate for replacement of equipment units but not at the current year.



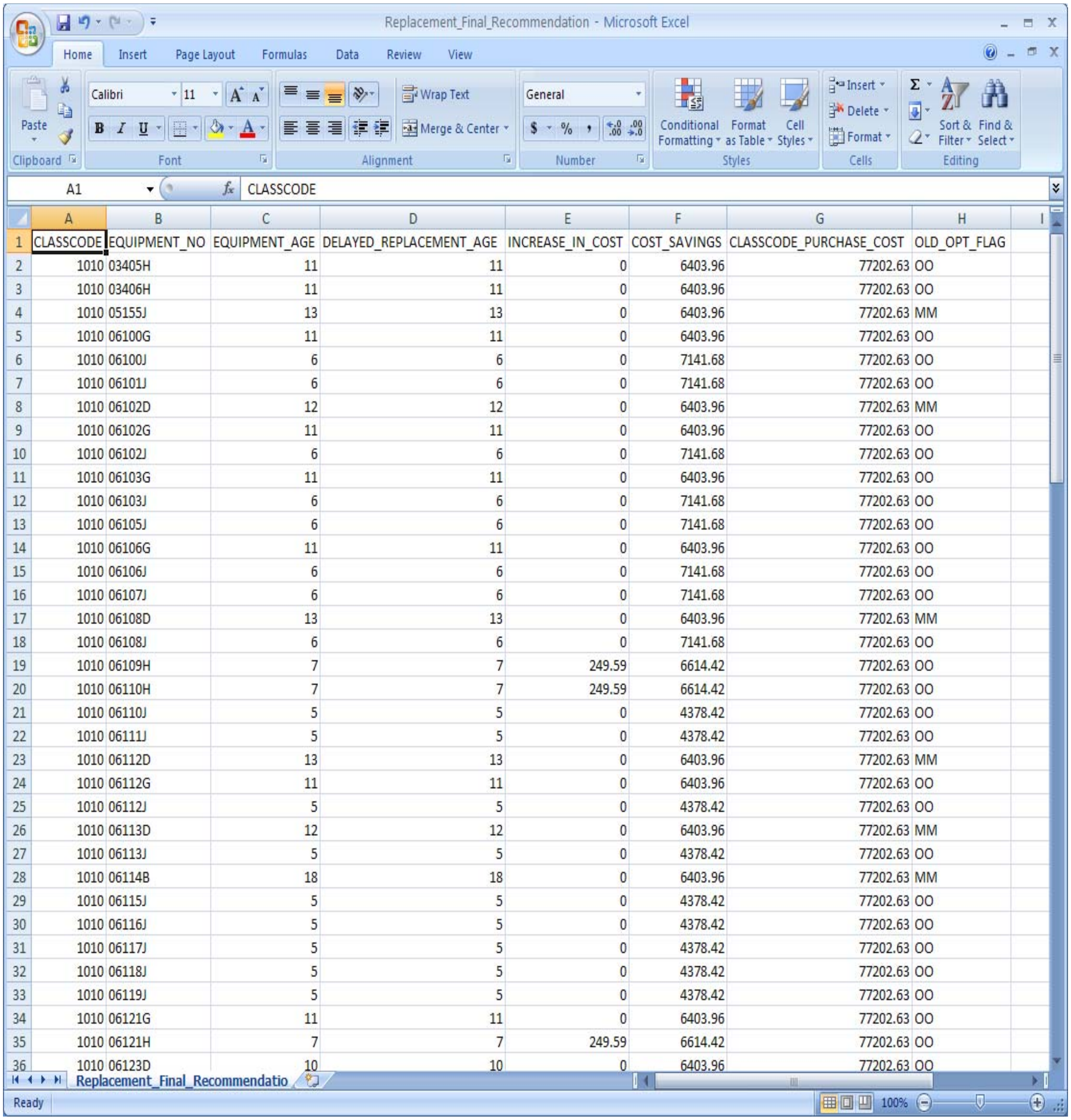
	A	B	C	D	E	F	G	H
1	CLASSCODE	EQUIPMENT_CODE	EQUIPMENT_AGE	DELAYED_REPLACEMENT_AGE	INCREASE_IN_COST	COST_SAVINGS	CLASSCODE_PURCHASE_COST	OLD_OPT_FLAG
2	1010	06130H	7	7	249.59	6614.42	77202.63	OO
3	1010	06130H	7	8	381.28	6482.73	78449.72	O
4	1010	06130H	7	9	587.92	6276.09	79716.95	O
5	1010	06130H	7	10	725.08	6138.93	81004.64	O
6	1010	06130H	7	11	684.61	6179.4	82313.14	O
7	1010	06130J	5	5	0	4378.42	77202.63	OO
8	1010	06130J	5	6	350.37	4028.05	78449.72	O
9	1010	06130J	5	7	783.28	3595.13	79716.95	O
10	1010	06130J	5	8	1054.97	3323.45	81004.64	O
11	1010	06130J	5	9	1182.38	3196.04	82313.14	O
12	1010	06130J	5	10	1352.39	3026.02	83642.78	O
13	1010	06130J	5	11	1397.41	2981.01	84993.89	O
14	1010	06131G	11	11	0	6403.96	77202.63	OO
15	1010	06131H	7	7	249.59	6614.42	77202.63	OO
16	1010	06131H	7	8	381.28	6482.73	78449.72	O
17	1010	06131H	7	9	587.92	6276.09	79716.95	O
18	1010	06131H	7	10	725.08	6138.93	81004.64	O
19	1010	06131H	7	11	684.61	6179.4	82313.14	O
20	1010	06131J	5	5	0	4378.42	77202.63	OO
21	1010	06131J	5	6	350.37	4028.05	78449.72	O
22	1010	06131J	5	7	783.28	3595.13	79716.95	O
23	1010	06131J	5	8	1054.97	3323.45	81004.64	O
24	1010	06131J	5	9	1182.38	3196.04	82313.14	O
25	1010	06131J	5	10	1352.39	3026.02	83642.78	O
26	1010	06131J	5	11	1397.41	2981.01	84993.89	O
27	1010	06131K	3	5	479.62	4058.2	79716.95	O
28	1010	06131K	3	6	914.52	3623.31	81004.64	O
29	1010	06131K	3	7	1218.52	3319.3	82313.14	O
30	1010	06131K	3	8	1478.53	3059.29	83642.78	O
31	1010	06131K	3	9	1651.53	2886.3	84993.89	O
32	1010	06131K	3	10	1788.08	2749.74	86366.83	O
33	1010	06131K	3	11	1866.44	2671.38	87761.95	O
34	1010	06132H	7	7	249.59	6614.42	77202.63	OO
35	1010	06132H	7	8	381.28	6482.73	78449.72	O
36	1010	06132H	7	9	587.92	6276.09	79716.95	O

Figure A.0.19: Delay.csv

A.4.2.4 Replacement_Final_Recomendation.csv

This file is arranged similarly to the file "Delay.csv" described in section A.4.2.3. However, it should be noted that this file is provided as the final optimized replacement solution recommended by the ERO software (which employs both DP optimization techniques in the first round and the Knapsack programming optimization in the second round) with the intention of maximizing the benefit for TxDOT, subject to the specified annual budget constraint.

Also, the sum of the Increase in Cost compared to the optimized decision, the Cost Savings versus the benchmark decision, and the total estimate of the ClassCode Purchase Costs are provided at the bottom of each column respectively.



	A	B	C	D	E	F	G	H
1	CLASSCODE	EQUIPMENT_NO	EQUIPMENT_AGE	DELAYED_REPLACEMENT_AGE	INCREASE_IN_COST	COST_SAVINGS	CLASSCODE_PURCHASE_COST	OLD_OPT_FLAG
2	1010	03405H	11	11	0	6403.96	77202.63	OO
3	1010	03406H	11	11	0	6403.96	77202.63	OO
4	1010	05155J	13	13	0	6403.96	77202.63	MM
5	1010	06100G	11	11	0	6403.96	77202.63	OO
6	1010	06100J	6	6	0	7141.68	77202.63	OO
7	1010	06101J	6	6	0	7141.68	77202.63	OO
8	1010	06102D	12	12	0	6403.96	77202.63	MM
9	1010	06102G	11	11	0	6403.96	77202.63	OO
10	1010	06102J	6	6	0	7141.68	77202.63	OO
11	1010	06103G	11	11	0	6403.96	77202.63	OO
12	1010	06103J	6	6	0	7141.68	77202.63	OO
13	1010	06105J	6	6	0	7141.68	77202.63	OO
14	1010	06106G	11	11	0	6403.96	77202.63	OO
15	1010	06106J	6	6	0	7141.68	77202.63	OO
16	1010	06107J	6	6	0	7141.68	77202.63	OO
17	1010	06108D	13	13	0	6403.96	77202.63	MM
18	1010	06108J	6	6	0	7141.68	77202.63	OO
19	1010	06109H	7	7	249.59	6614.42	77202.63	OO
20	1010	06110H	7	7	249.59	6614.42	77202.63	OO
21	1010	06110J	5	5	0	4378.42	77202.63	OO
22	1010	06111J	5	5	0	4378.42	77202.63	OO
23	1010	06112D	13	13	0	6403.96	77202.63	MM
24	1010	06112G	11	11	0	6403.96	77202.63	OO
25	1010	06112J	5	5	0	4378.42	77202.63	OO
26	1010	06113D	12	12	0	6403.96	77202.63	MM
27	1010	06113J	5	5	0	4378.42	77202.63	OO
28	1010	06114B	18	18	0	6403.96	77202.63	MM
29	1010	06115J	5	5	0	4378.42	77202.63	OO
30	1010	06116J	5	5	0	4378.42	77202.63	OO
31	1010	06117J	5	5	0	4378.42	77202.63	OO
32	1010	06118J	5	5	0	4378.42	77202.63	OO
33	1010	06119J	5	5	0	4378.42	77202.63	OO
34	1010	06121G	11	11	0	6403.96	77202.63	OO
35	1010	06121H	7	7	249.59	6614.42	77202.63	OO
36	1010	06123D	10	10	0	6403.96	77202.63	OO

Figure A.0.20: Replacement_Final_Recomendation.csv

APPENDIX A.A: DEFINITIONS OF INPUT DATA ELEMENTS

For the convenience of the descriptions, the following notations are used. For example, if the file named X contains elements Y and Z, then it is described as:

File_Name_X;
  Element_Y
  Element_Z

  DISCRIPTION OF ELEMENT.

All notions will follow.

Add_Replacement_Code;
  Add_Replacement_Code
  Add_Replacement_Code_Desp

  THIS ELEMENT SPECIFIES WHETHER THE NEW ITEM IS TO REPLACE A UNIT BEING RETIRED OR IF THE NEW UNIT IS AN ADDITION TO THE EXISTING FLEET. CODE VALUES ARE:
  A = ADDED EQUIPMENT
  R = REPLACING OLD EQUIPMENT

Equip_Status;
  Equip_Status
  Equip_Status_Desp

  THIS ELEMENT SPECIFIES THE CURRENT STATUS OF THE SPECIFIC EQUIPMENT ITEM. THE STATUS ITEM IS ACTIVE, RETIRED, TRADED, ETC. CODE VALUES ARE:
  P = PURCHASE ORDER PROCESSED
  Q = REQUISITIONED
  R = RECEIVED
  S = SURPLUS
  V = VOUCHER PROCESSED
  W = WAITING DISPOSITION
  X = RETIRED EQUIPMENT, PAYMENT PENDING
  Y = PENDING REPLACEMENT
  Z = RETIRED (SEE RETIREMENT-CODE)

Use_Unit_Code;
  Use_Unit_Code
  Use_Unit_Code_Desp

THIS ELEMENT INDICATES THE MANNER OF TABULATING USAGE; IN MILES OR HOURS. CODE VALUES ARE:
01 = MILE
02 = HOUR

Class_Code;
CLASS_CODE
CLASS_CODE_DESC

THIS ELEMENT IS USED AS AN INDICATOR CODE TO DEFINE THE CLASS TO WHICH THE EQUIPMENT ITEM BELONGS. CODE VALUES CAN BE FOUND IN APPENDIX B.

Retirement_Code;
Retirement_Code
Retirement_Code_Desc

THIS ELEMENT SPECIFIES HOW AN ITEM OF RETIRED EQUIPMENT WAS RETIRED. CODE VALUES ARE:
1 = TRADE-IN
2 = SOLD
3 = CONDEMNED AND DISMANTLED
4 = STOLEN
5 = GIVEN NEW EQUIPMENT NUMBER
6 = CHANGED TO MINOR
7 = SOLD-AUCTION
8 = INTER-AGENCY TRANSFER
9 = NEGOTIATED SALE

Body_Style;
Body_Style
Body_Style_Desc

THIS ELEMENT SPECIFIES THE STYLE TYPE OF THE BODY OF THE EQUIPMENT ITEM. CODE VALUES ARE:
00 = DEL ERRONEOUS ENTRY
01 = PICKUP
02 = BOLT ON COMPARTMENTS
03 = UTILITY SERVICE
10 = DUMP, PICKUP
11 = DUMP, STAKE
12 = DUMP, PLATFORM
13 = DUMP, EJECTION

16 = VAN
17 = PANEL
20 = PLATFORM
21 = STAKE
25 = REFUSE COLLECTION
26 = OILFIELD
27 = TANK
40 = TILT BED, LEVEL DECK
41 = TILT BED, BVR TAIL
42 = FIXED BED, LVL DECK
43 = FIXED BED, BVR TAIL
50 = GOOSENECK, FXD,LVL D
51 = GOOSENECK, FXD,DRP D
52 = GOOSENECK, FLD,LVL D
53 = GOOSENECK, FLD,DRP D
54 = DUMP, TRAILER
60 = POLE
61 = FLOAT
62 = STAKE FLOAT
63 = PANEL FLOAT
64 = SIGN TRANSPORT
65 = DUMP BODY

Fuel_Type;
Fuel_Type
Fuel_Type_Desc

THIS ELEMENT IDENTIFIES THE SPECIFIC TYPE OF FUEL USED TO POWER THE MAIN ENGINE OF THE EQUIPMENT ITEM. CODE VALUES ARE:
B = BIO-DIESEL
C = CNG
D = DIESEL
E = ELECTRIC
F = FLEX FUEL
G = GASOLINE
H = HYBRID
K = KEROSENE
L = LPG
M = METHANOL
N = DED CNG
P = DED LPG
W = WAIVERED
Y = HYDROGEN
0 = DEL ERROR

Steering_Type;

Steering_Type
Steering_Type_Desc

THIS ELEMENT SPECIFIES THE TYPE OF STEERING AVAILABLE ON THE EQUIPMENT ITEM.
CODE VALUES ARE:
C = CLUTCH
H = HYDROSTATIC
M = MANUAL
P = POWER
0 = DEL ERROR

Brake_Type;

Brake_Type
Brake_Type_Desc

THIS ELEMENT SPECIFIES THE TYPE OF BRAKES CURRENTLY INSTALLED UPON THE EQUIPMENT ITEM. CODE VALUES ARE:
A = STRAIGHT AIR
D = DYNAMIC, HYD
E = ELECTRIC
H = HYDRAULIC
M = MECHANICAL
P = POWER ASSIST
S = SURGE, HYD
0 = DEL ERROR

Trans_Type;

Trans_Type
Trans_Type_Desc

THIS ELEMENT SPECIFIES THE TYPE OF TRANSMISSION. CODE VALUES ARE:
A = AUTOMATIC
H = HYDROSTATIC
M = MANUAL
O = OTHER
P = POWER SHIFT
0 = DEL ERROR

Equip_Capa;

Equip_Capa
Equip_Capa_Desc

THIS ELEMENT INDICATES THE MEASUREMENT TYPE (CUBIC YARDS, FEET, TONS, ETC) USED TO DEFINE THE EQUIPMENT CAPACITY. CODE VLUES ARE:
00 = DEL ERROR
01 = POUNDS
02 = CUBIC YARDS
03 = GALLONS
04 = FEET
05 = TONS
06 = INCHES
07 = CUBIC FT/MIN
08 = FEET/MINUTE
09 = CUBIC FEET
10 = DOORS
11 = HORSEPOWER
12 = GALLONS/MIN
13 = CARS-FERRY

Make_Code;
Make_Code
Make_Code_Desc

THIS ELEMENT IS USED TO IDENTIFY THE SPECIFIC 'MAKE' OF THE EQUIPMENT ITEM. CODE VALUES ARE:

1 AISIN
2 ADDCO
3 ACKER
4 ACTON
5 AIRPLACO
6 ALLISON
7 ADAMS
8 ARGO
9 ALERT ARROW
10 AEROIL
11 ALL MARK
12 ADVANCE
13 ALEMITE
14 ALENCO ALBRITTEN ENG. CO.
15 ALLIS-CHALMERS
16 AMC (AMERICAN MOTORS CORP)
17 AMIDA
18 AMTEX
19 ALTEX
20 AMERICAN CRANE
21 ALTEC
22 AEROLIFT
23 AMERICAN SIGNAL
24 AMERICAN HOIST & DERRICK CO
25 ANTHONEY
26 ALAMO
27 ACE WELDING & TRAILER CO.
28 ARAN
29 ARMLIFT
30 APOLLO SYSTEM II
31 ARMY SURPLUS
32 ARROSTAR
33 ARROW
34 ASPLUNDH
35 ARROW MASTER
36 ASTRON CORP
37 ARROW PLUS
38 ATHENS
39 AMERICAN BODY
40 ATLAS
41 ATOKA
42 ASPEN AERIALS
43 AUSTIN-WESTERN
44 AMERI-TRAIL
45 ACCURATE
46 AQUA-DYNE
47 AUTOCAR
48 AUTO CRANE
49 AMERICAN EQUIPMENT & TRAILER
50 AVIATION
51 BADGER
52 BAKER
53 ASPHALT ZIPPER INC.
54 ALLIANZ MADVAC
57 BALDERSON
58 BEECHCRAFT
59 BANDIT INDUSTRIES
60 BARRIER SYSTEMS
61 BARTELL
62 BARKO
63 BARNES
64 BAUGHMAN
65 BEDELL
66 BEAN(JOHN
67 BEMIS
68 BELSHE
69 BERKLEY
70 BEARCAT
71 BARBER-GREENE
72 BERRY
73 BEST
74 BASIC HEAVY HAULER
75 BINKS
76 BIRMINGHAM
77 BENDI
78 BLACKWELL
79 BLANCHET
81 BLAW-KNOX
82 BIG TEX
83 BITELLI-AMERICA
86 BMC
87 BMCO
88 BOSCH
89 BOBCAT
90 BORG WARNER
91 BOLENS
92 BOMAG
93 BRIGGS & STRATTON
94 BOWIE
95 BRILLION
96 BROS MFG CO
97 BROCE MFG CO
100 BRODERSON
101 BRUSH BANDIT
102 BUCKEYE
117 BURCH
118 BUSH-WHACKER
119 BUTLER
120 BUSH HOG
121 DEALER TRUCK EQUIP
126 CUB CADET
127 CALDWELL
128 CTS (CONSTRUCTION TRLR SPEC
129 CAPITOL
130 CARTER
131 CARAVELLE
133 CARVER
134 CASE
135 CASELL
136 CASE-INTERNATIONAL
139 CATERPILLAR
142 CIRCLE D
143 CESA
144 C.E.I. INC.
145 CESSNA
146 CECO
147 CEDARAPIDS
148 CEMEN TECH INC.
149 CHAMPION
150 CHARGER
151 CHALLENGER
152 CPS
153 CORE CUT
154 CHAUSSE
155 CRYSTEEL
156 CIMLINE
157 C. H. & E. MFG CO
158 CHIPARVESTOR
159 CLARK MICHIGAN
160 CHEVROLET
161 CHIEF
162 CHILDERS MFG. CO. INC.
163 CHICAGO-PNEUMATIC
164 CHRYSLER
165 CHIPMORE
166 CLARK
167 CIMCEAL
168 CIBOLO
169 CLEAVER-BROOKS
170 CLIPPER
171 CLEMENT
172 CMC CONSTRUCTI ON MCY COR
173 CTI CONSTRUCTI ON TECH.
174 CMI
175 CLEVELAND
176 CORBETT BROS. STEEL CO.
177 CONTINENTAL
178 CME (CENTRAL MINE EQUIP)
179 CORSICANA
180 CRAFCO
181 COMMERICAL BODY CORP.
182 CONSOLIDATED DIESEL ELECTRIC
183 CRC (CRUTCHER-ROLF-CUMMIN)
184 CROWN
185 CORMOR
186 COKER ENTERPRISES
187 CLUB CAR
188 CLIFTON METAL PRODUCTS, INC.
189 CRYSTEEL
190 CUSHMAN
191 CONDOR
192 CMS
193 CUMMINS
194 C-W
195 DAKOTA TRAIL-EZE
196 DALE PHILLIPS
197 DALLAS TANK
198 DAEWOO
199 DAMCO
200 DANA
201 DANDL
202 DANCO
207 DATSON
208 DAVEY
209 DAVIS
211 JOHN DEERE
212 DEALERS TRUCK EQUIPMENT
213 DEXTER
214 DEALERS
216 DETROIT DIESEL
217 DEVERE
218 DEUTZ
219 DEVILBISS
220 DIETZ
222 DIAMOND T
223 DITCH WITCH
224 DISPENSING TECHNOLOGY CORP
225 DODGE
226 DISPLAY SOLUTIONS
227 DOOSAN
234 DORSEY
235 DOWNS-CLARK
236 DOWNING
237 DRESSON
238 DRESSTA (DRESSER
239 DURAMAX
240 DROTT
243 DUTEC
244 DUNCAN
245 DURALE
246 DUPLEX
247 DUR-A-LIFT
248 DYNAPAC
249 DYNAFLECT
250 DYNATEST
251 ECONOPAK
252 EDCO
253 ECOLOTEC
254 EATON
255 EAGER BEAVER
256 EASI-SIGN
257 EJECTO
258 ELANCHET
259 ELDER
260 ELEPHANT-VAC
261 EAGLE
262 ELGIN
263 EAGLE BODY
264 ELLIOTT
265 ENGLER (SMC/TERRAIN KING)
266 EASTERN TECHNOLOGIES LTD
269 ESCOTT
270 ESSICK
271 E.R. BUSKE MFG CO INC
272 EVACO SUPERLINE
273 ETNYRE
274 EQUIPMENT TECHNOLOGY
275 EXCEL
276 E-Z GO
277 FAILING
278 FABCO
280 FAIR SNOCRETE
296 FLEX-O-LITE
297 FEDERAL CONSTRUCTION PRODUCTS
298 FEIGELSON
299 F & F
300 FERGUSON
301 FINN
302 FLEXIBLE
303 FLAHERTY
304 FLINK
305 FLEX-LIFT
306 FIATALLIS
307 FLEET
308 FLYNN
309 FMC
310 FORD
311 FONTAINE
312 FIAT-IVECO
313 FLAG
314 FREIGHTLINER
317 FT WORTH STR ST
318 FT. WORTH TRUCK
319 FOSTER
320 FWT
321 FUNK
322 FRUEHAUF
323 FULLER
324 F W D
325 GMC
326 GALION-DRESSER
327 GANDY
330 GARDNER-DENVER
331 GARWOOD
332 GENIE
333 GEARCO
334 GEMCO
335 GEHL
336 GEFFS
337 GENERAL
338 GEOMEDIA RESEARCH & DEVLP.
341 GILSON
345 GLEDHILL
351 GOOD ROADS
352 GOOSENECK
353 GOMACO
354 GORBETT BROS.
357 GORMAN RUPP
360 GRACE
361 GRIMMER-SCHMIDT
362 GRACO
363 GRADALL
364 GRASSHOPPER
365 GREAT PLAINS
368 GRAVELY
369 GROVE
370 GRIFFIN
371 GULF
372 G & W
380 HATZ
381 HUSQVARNA
382 HAMM
383 HAMCO HADDOX
384 HARLO
385 HAMILTON
386 HASSELL
387 HARSH
388 HAULETTE
389 HATZ
390 HAYES
391 HOLDEN
392 HYUNDAI
393 HEIL
394 HYDRA
395 HENKE
396 HI-VU
397 HERBICIDE
398 HERCULES
399 HESSTON
400 HOFFMAN
401 HORMAN
402 HIGHLIFT
403 HI-RANGER
404 HI-WAY
405 HI-WAY SAFETY SUPPLY
406 HONDA
407 HOBBS
408 HOUCK
409 HOLAN
410 HOUGH
411 HY TRAK
412 HOWARD
413 HOPTO
414 HOWLAND
415 HP SYSTEMS
416 HYDRO MATIK
417 HUBER
418 HUTCHEN
419 HUGHES-KEENAN
420 HUSKY
421 HYDRA LIFT
422 HYDRO-BROOM
423 HYSTER
424 HYDROBLASTER
425 HYDROMATIC
426 ICUBOTA
427 IMMSA
428 IMCO
429 IHC INTNL HARVESTER
430 INTERNATIONAL (NAVISTAR)
431 INTERNATIONAL TRAFFIC SYSTEMS
435 INGERSOLL RAND
439 INGRAM
443 INSLEY
444 INTERSTATE
445 ISUZU
446 ITL
447 IVECO
450 J & I
451 J & L
455 JACOBSEN
458 JACUZZI
461 JAEGER
462 JATCO
463 JAHN
464 J C B
465 JLG
466 JONES TRAILER CO.
467 JEEP
468 JOHNSTON
472 JOY
473 K & K SYSTEMS INC.
474 KHI
475 K.C. WELDING
476 KALYN
477 KARRI-GO
478 KAST
479 KAWASAKI
480 K D MANITOU
481 KDC
482 KERESTINE
483 KELLEY CRESWELL
484 K. J. LAW ENGINEERS
485 KEYSTONE
486 KOENIG
487 KING
488 KINGHAM
489 KLEIN
490 KNAPHEIDE
491 KIEFER
492 KOBELCO
493 KOR-IT
494 KOEHRING
495 KOHLHASS
496 KUT-KWICK
497 KWIK MIX
498 KURB-KUTTER
499 KUHN
500 KOLBERG
501 KOMATSU
503 KOHLER
504 KUBOTA
505 LANDPRIDE
506 LANE-WELLS
508 LARSON/TERRAIN KING
510 LAYTON
511 LECO
512 LEAR-SIEGLER
513 LECTRO-LIFT
514 LELAND

Figure A.21 Make Code Values.

515 LEE-BOY
516 LEROI
517 LEE
518 LINELAZER
519 LIFT KING
520 LIFT-A-LOFT
521 LINEAR DYNAMICS (PRISMO)
522 LINE MASTER
523 LIBERTY
524 LIFT-ALL
525 LIMA
526 LIFTMOORE
527 LIME MASTER
528 LISTER
529 LINK-BELT (FMC)
530 LITTER GITTER
531 LITTLEFORD
532 LOMBARDINI
533 LINAX
534 LITTLE GIANT
535 LIEBHERR
536 LINDE
537 LOADCRAFT
538 LORAIN
539 LONGYEAR
540 LOAD KING
541 LONG
542 LUBBOCK
543 LTI - LAKE TECHNOLOGIES INC.
544 LINCOLN
545 LINAMAR
546 LUFKIN
547 LOAD-TRAIL
554 MAC'S CUSTOM FIBERGLASS
555 MACK
556 MADDISON
557 MARK RITE
558 MARK IV
559 MARLOW
560 MARLISS
561 MANCHESTER/WESSEL
565 MARCO
566 MAZDA
567 MASTER CRAFT
570 MATHEWS, CORP.
571 MEI MARCATO ENT
572 MAYCO
573 MAULDIN
574 MASSEY-FERGUSON
575 MCCABE-POWERS
576 MERITOR
577 MERCEDES
578 MESSAGE DIRECTOR
581 M-C MATHEWS CO.
582 MEYER
583 METAL FABRICATING CO.
584 MELROE
585 MICHIGAN
589 MIDLAND
591 MIDWEST
594 MB
596 MILLER
599 MITSUBISHI
600 MINN-MOLINE
601 MOORE VENTURES
602 MITTS & MERRILL
603 MORBARK
604 ATHEY-MOBIL
605 MOBILIFT
606 MODERN WELDING
607 MONO
608 MOOG
609 MOHAWK
610 MOWALL
611 MODERN, INC.
612 MOTT
613 MORRISON
614 MO-TRIM
615 MONROE-PATTERSON
616 MONROE
617 MOSSPOINT MARINE
618 MORGAN
619 MULLER
620 MTI
621 MURPHY
622 MUNCIE
623 MQ POWER
627 NABORS
628 NOBLE
629 NATIONAL SIGNAL INC.
630 NATIONAL
631 NEW PROCESS
632 NEW HOLLAND
633 NORTHFLD HUSKY
634 NORTHWEST SHOVEL CO
635 NISSAN
636 NEW VENTURE
637 NUTTALL
638 NUMAR
640 OKAMURA
641 OMC
642 OILFIELD
643 OMAHA
644 ONAN
645 OLIVER
646 OVER-LOWE
647 OMNI
648 OPTO VISION
649 OWENS
650 OWN
651 PACK-IT
652 PACIFIC PUMP CO
653 P & H
654 PANHANDLE STEEL
655 PAXTON-MITCHELL
656 PACEMATE
657 PARTEK
658 PERFECTION
659 PATTERSON
660 PEERLESS
661 PERKINS
662 PERFECT
663 PARISH
664 PETTIBONE-MERCURY
665 PETTER
666 PETTIBONE-MULLIGEN
667 PAVE-MARK
668 PETTIBONE-WOOD
669 PHELAN (TRAILERS
670 PEUGEOT
671 PARKHURST
672 PACE
673 PIERCE
674 PIERCE-BEAR
675 PIPE HUNTER
676 PIONEER
677 PIPER
678 PARKER
680 PITMAN
682 PRECISION DESIGN
683 PONTIAC
684 PLYMOUTH
685 PRO-PATCH
687 PORTA-PATCHER
688 POWERSHUTTLE
689 POWER CURBERS INC
690 POWER PLUS, INC.
691 POWERS
692 POWER BOSS
693 PRECISION SOLAR CONTROLS INC.
694 POWER QUEST
696 PRIME-MOVER
697 PRISMO (LINEAR DYNAMICS
698 PUCKETT BROS MFG. CO.
699 PYLES
700 PRODUCTION DIGGERS INC
702 QUICKWAY
703 ROADMASTER
704 QUINCY
705 RADIAN
706 RAYMON
707 RAWSON-KOENIG
708 RANGER
709 RAYGO
710 REFRACT-ALL
711 RANSOMES
712 REINCO
713 REXROTH
714 RANCH KING
715 REACH ALL
716 RAINHART
717 REPUBLIC
718 REX
719 RHINO
720 READING
721 RENCO
722 RENAULT
723 ROBIN
724 ROCKWELL
725 RETESA
726 RHEA'S
728 ROLCOR
732 ROME
735 ROPER
739 ROSCO
740 ROTARYAIRE
741 RPM TECH
748 ROYAL
749 ROSS
750 ROYAL MATHIESSEN
751 ROYAL INDUSTRIES
752 RUSSELL
753 ROTECH
754 RUGBY
755 SCHWARZE SUPERVAC
756 SAMPSON
757 SALISBURY
758 SAFETY SHEAR
759 SCHIELD-BANTAM
760 SCHRAMM
761 SAUER
762 SAMSUNG
763 TAKE 3
765 SEAMAN
769 SERVIS
770 STAHL
771 SILENT HOIST
772 SIGNAL
775 SKYTEL
776 SHOOK
777 SHUTTLELIFT
778 SHOP BUILT
779 SHOP BUILT (GSD
780 SIMPLICITY
781 SKY-DART
782 SKYVAN
783 SLAUTTERBACK
784 SLOPE MASTER
785 SKYJACKER
786 SLOPEMOWER
787 SIMCO
789 SLUSHER MCCLEAN
790 SMC-MOWAL
791 SMITH
792 SNOWBIRD
793 STAMM
794 SUPERIOR BROOM
795 SUKUP
796 STEINER
797 SPILLARS
798 SNOGO
799 SNOWCO
800 SOUTHWEST
801 SOLRTRON INTERNATIONAL
802 SOLAR TECHNOLOGY
803 SUPER PRECISION DESIGN INC
804 SPENCER MACHINE SHOP
805 SPENCER MARSH
806 SPENCER-SAFFORD
807 SPICER
808 STEPP
809 S & R
810 STAHL
811 STAFFA
812 SUNRAY
813 STANDARD STEEL WORKS
814 STAR TANK & TRAILER
815 STERLING
816 STELCO
817 STEPHENS-CANFIELD
818 SUNDANCE
819 STONE
820 STOCKLAND
821 STREETERAMET
822 SUPREME
823 SULLAIR
824 SULLIVAN
825 SUNSTRAND
826 SUNSHINE
827 SUZUKI
828 SWENSON
829 SWEEPSTER
830 SWIZ
831 TCD (TRAFFIC CONTROL DEVICES
832 TAIT
833 TAMPO
834 TCM
835 TECUMESH
836 TARGET
837 TARCO HIGHLANDER
838 TELELECT
839 TAYLOR(GW
840 TECO
841 TENNANT
842 TEALE
843 TERRAIN KING
844 TEXOMA
845 TDCJ-TX DEPT OF CRIM JUSTICE
846 TESCO
847 THRUN
848 THS
849 TIMCO
850 TEXAS TRANSPORT
851 TIMKEM
852 TIME
853 TMT
854 TOYOSHA
855 TORO
856 TOWERS
857 TPE
858 TOWNMOTOR
859 TOW MOTOR
860 TRACTOMOTIVE
861 TOYO
862 TOYOTA
863 TRADEWINDS, IND.
864 TRAILMOBILE-LAP
865 TRAILER INDUSTRIES, INC.
866 TRANSPORT
867 TRAIL-EZE
868 TRANSPORT TRAILER
869 TRANSAXLE
870 TRANTEX
871 TSI (TRANSPORT SYSTEMS, INC
872 TRAFFIC CONTROL DEVICE
873 TUFF
874 TRAIL KING
875 TRENCH-LINER
876 TRIUMPH
877 TROJAN
878 TYMCO
879 TYE
880 THOMPSON (TPM
881 UNDETERMINED MAKE
882 UEC MFG CO
883 UNI-HOIST
884 UNIMASCO
885 UNION CITY BODY CO.,INC.
886 VME
887 VOLVO BM
888 TAYLOR-DUNN
889 TELEDYNE
890 VERMEER
891 VAN WAMEL
892 TRAILBOSS
893 UPRIGHT
894 VALK
895 VEPED
896 UTILITY
897 VERSALIFT
898 VIBRANT
899 VINA NATIONAL
900 VIBRO-PLUS
901 VINA-FLASH
902 VICKERS
903 VIKING
904 WABCO
905 WALDON
906 WALDON VERSA
907 WALD
908 WALES
909 WALKIE
910 WANCO
911 WAKELAND
912 WAAW
913 TRAILNOR
914 WARNER
915 WALTCO
916 VER-MAC
917 VOELLER
918 WAUKESHA
919 WAUSAU
920 VIBROMAX
921 TCI-PMF
922 TEREX
923 WAYNE
924 TOP HAT
925 WEDGE
926 VACTOR
927 WELLS CARGO
928 WENDLAND
929 VOGELE
931 WESTERN
935 WHEELER
936 WHEEL HORSE
937 WHEELED ROLLER
943 WHITE - GMC
946 W. H. MFG. CO.
949 WILLIAMS
952 WILLYS (JEEP
956 WILSHIRE
959 WINK-O-MATIC SIGNAL CO.
962 WIRTGEN
963 WISCONSIN
964 WISE
965 WOODCHUCK
966 WOODS
971 WORK AREA PROTECTION CORP
972 WORTHINGTON
980 WYLIE
981 W W TRAILER
986 YALE
987 YAZOO
989 YANMAR
990 YUKON
991 ZAHNKADFABRIK-PASSAU
992 ZF
993 ZIMMERMAN
999 UNKNOWN

Figure A.22 Make Code Values - Cont.

Dist_Div;

Dist_Div
Dist_Div_Desc

THIS ELEMENT IDENTIFIES THE DISTRICT WHICH OWNS THE EQUIPMENT.
CODE VALUES ARE:
01 = PARIS
02 = FORT WORTH
03 = WICHITA FALLS
04 = AMARILLO
05 = LUBBOCK
06 = ODESSA
07 = SAN ANGELO
08 = ABILENE
09 = WACO
10 = TYLER
11 = LUFKIN
12 = HOUSTON
13 = YOAKUM
14 = AUSTIN
15 = SAN ANTONIO
16 = CORPUS CHRISTI
17 = BRYAN
18 = DALLAS
19 = ATLANTA
20 = BEAUMONT
21 = PHARR
22 = LAREDO
23 = BROWNWOOD
24 = EL PASO
25 = CHILDRESS
29 = CAMP HUBBARD
44 = GENERAL SERVICES DIV

Inflation_Table_YR;

YEAR DATA_INFL_RATE INFLATION_RATE

YEAR	DATA_INFL_RATE	CAL_INFL_RATE	YEAR	DATA_INFL_RATE	CAL_INFL_RATE
1913	**21.85**	21.85000	1962	**7.16**	4.52661
1914	**21.63**	21.15918	1963	**7.07**	4.38349
1915	**21.42**	20.49020	1964	**6.98**	4.24490
1916	**19.85**	19.84237	1965	**6.87**	4.11069
1917	**16.9**	19.21503	1966	**6.68**	3.98073
1918	**14.33**	18.60751	1967	**6.48**	3.85487
1919	**12.5**	18.01921	1968	**6.22**	3.73299
1920	**10.82**	17.44950	1969	**5.89**	3.61497
1921	**12.09**	16.89781	1970	**5.58**	3.50068
1922	**12.88**	16.36356	1971	**5.34**	3.39000
1923	**12.65**	15.84620	1972	**5.18**	3.28282
1924	**12.65**	15.34520	1973	**4.87**	3.17903
1925	**12.36**	14.86004	1974	**4.39**	3.07852
1926	**12.22**	14.39022	1975	**4.02**	2.98119
1927	**12.43**	13.93525	1976	**3.8**	2.88693
1928	**12.65**	13.49467	1977	**3.57**	2.79566
1929	**12.65**	13.06801	1978	**3.32**	2.70727
1930	**12.95**	12.65485	1979	**2.98**	2.62167
1931	**14.23**	12.25475	1980	**2.63**	2.53879
1932	**15.79**	11.86729	1981	**2.38**	2.45852
1933	**16.64**	11.49209	1982	**2.24**	2.38079
1934	**16.14**	11.12875	1983	**2.17**	2.30552
1935	**15.79**	10.77690	1984	**2.08**	2.23262
1936	**15.56**	10.43617	1985	**2.01**	2.16204
1937	**15.02**	10.10622	1986	**1.97**	2.09368
1938	**15.34**	9.78669	1987	**1.9**	2.02748
1939	**15.56**	9.47727	1988	**1.83**	1.96338
1940	**15.45**	9.17763	1989	**1.74**	1.90131
1941	**14.72**	8.88747	1990	**1.66**	1.84119
1942	**13.27**	8.60648	1991	**1.59**	1.78298
1943	**12.5**	8.33437	1992	**1.54**	1.72661
1944	**12.29**	8.07087	1993	**1.5**	1.67202
1945	**12.02**	7.81570	1994	**1.46**	1.61916
1946	**11.09**	7.56859	1995	**1.42**	1.56797
1947	**9.7**	7.32930	1996	**1.38**	1.51839
1948	**8.98**	7.09757	1997	**1.35**	1.47039
1949	**9.09**	6.87317	1998	**1.33**	1.42390
1950	**8.98**	6.65587	1999	**1.3**	1.37888
1951	**8.32**	6.44543	2000	**1.26**	1.33528
1952	**8.16**	6.24165	2001	**1.22**	1.29307
1953	**8.1**	6.04431	2002	**1.2**	1.25218
1954	**8.04**	5.85321	2003	**1.18**	1.21259
1955	**8.07**	5.66815	2004	**1.15**	1.17426
1956	**7.95**	5.48894	2005	**1.11**	1.13713
1957	**7.7**	5.31540	2006	**1.07**	1.10118
1958	**7.49**	5.14735	2007	**1.04**	1.06636
1959	**7.43**	4.98461	2008	**1**	1.03265
1960	**7.31**	4.82701	2009	**1**	1.00000
1961	**7.24**	4.67440			

Figure A.23 Consumer Price Index Inflation Rate Data.

APPENDIX A.B: TXDOT TERM – CLASSCODE DESCRIPTIONS AND BENCHMARK RULES

Table A.B.1: TxDOT Equipment Replacement Model Data

The TxDOT Equipment Replacement Model (TERM) uses historical data to identify candidates for replacement one year in advance of delivery. The purpose of early identification is to allow the districts time to identify the units for replacement; budget for replacement; allow GSD (Fleet Management and Purchasers) time to develop the specification; advertise and award the purchase; allow the vendor time to build the unit; and get it delivered to the district. This process may take up to one year. Therefore, keeping the units until the time of delivery, rather than early identification, will in fact hold the units in operation for up to a year under very expensive repair and operating costs. In reality, this would void any benefit of replacement analysis.

For comparative purposes, the class listing shows that point in life when it is identified by TERM, and where the unit would probably be when retired.

Shading/Bold Indicates Revisions

TxDOT EQUIPMENT REPLACEMENT MODEL (TERM) AS OF 10/08/2008

		USAGE		AGE		REPAIR
CLASS CODE	CLASS CODE DESCRIPTION	TERM STANDARD	AT DISPOSAL	TERM AGE	AT DISPOSAL	TERM REPAIR
001010	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, TO 29', INC TRUCK	7,000 HRS	8,000	7 YRS	8 YRS	75%
001020	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 30-39', INC TRUCK	7,000 HRS	8,000	7 YRS	8 YRS	75%
001030	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 40-59', INC TRUCK	7,000 HRS	8,000	7 YRS	8 YRS	75%
001040	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 60' +, INC TRUCK	9,000 HRS	10,000	10 YRS	11 YRS	50%
001050	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, MILEAGE	110,000 MI	120,000	7 YRS	8 YRS	100%
011010	ASPHALT DISTRIBUTOR, TRUCK MOUNTED, (INCLUDES TRUCK)	5,000 HRS	5,500	12 YRS	13 YRS	75%
012010	ASPHALT MAINTENANCE UNIT, 600 GAL, TRAILER MOUNTED	3,500 HRS	4,000	10 YRS	11 YRS	75%
012020	ASPHALT MAINTENANCE UNIT, 1000 GAL, TRAILER MOUNTED	**3,000 HRS**	**3,500**	12 YRS	13 YRS	75%
012030	ASPHALT MAINTENANCE UNIT, TRUCK MOUNTED	5,000 HRS	5,500	12 YRS	13 YRS	75%
012040	ASPHALT MAINTENANCE UNIT, DUMPBODY CONTAINED	4,500 HRS	5,000	13 YRS	14 YRS	75%
014000	ASPHALT MELTING KETTLE (HTR), TRAILER MOUNTED	1,800 HRS	2,000	10 YRS	11 YRS	75%
019000	ASPHALT RECLAIMER/STABILIZER, CLASS I, SP, < 94.5 CUT WIDTH	3,000 HRS	3,300	10 YRS	11 YRS	50%
020020	AUTOMOBILES, SEDAN, 100 THRU 112.9 IN. WHEELBASE	90,000 MI	100,000	8 YRS	9 YRS	**75%**
020030	AUTOMOBILES, SEDAN, 113 IN. WHEELBASE AND GREATER	90,000 MI	100,000	8 YRS	9 YRS	**75%**
025010	AUTOMOBILES, STATION WAGONS, UP TO 112.9 IN. WHEELBASE	90,000 MI	100,000	8 YRS	9 YRS	**75%**
044000	EARTH BORING MACHINE, TRUCK MOUNTED (INCLUDES TRUCK)	5,000 HRS	5,500	14 YRS	15 YRS	75%
052010	CRANE, CARRIER MOUNTED, CABLE OR TELESCOPING	6,000 HRS	6,300	16 YRS	17 YRS	75%
052020	CRANE, CRAWLER TYPE, CABLE CONTROL	10,000 HRS	11,000	14 YRS	15 YRS	50%
054000	CRANE, TELESCOPING BOOM, TRUCK MOUNTED (INCLUDES TRUCK)	7,000 HRS	8,000	12 YRS	13 YRS	50%
056000	CRANE, YARD/INDUSTRIAL, SELF PROPELLED	5,000 HRS	5,500	12 YRS	13 YRS	50%

064000	DYNAMIC DEFLECTION SYSTEM, TRAILER MOUNTED	90,000 MI	100,000	10 YRS	11 YRS	100%
070010	EXCAVATOR, HINGED OR TELESCOPING BOOM, CRAWLER TYPE	7,000 HRS	8,000	10 YRS	11 YRS	50%
070020	EXCAVATOR, HINGED BOOM, PNEUMATIC TIRED CARRIER	7,000 HRS	8,000	10 YRS	11 YRS	50%
075010	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS I	**6,000 HRS**	**6,500**	9 YRS	10 YRS	75%
075020	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS II	**6,000 HRS**	**6,500**	9 YRS	10 YRS	75%
075030	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS III	8,400 HRS	9,000	12 YRS	13 YRS	75%
080000	FORKLIFT, ELECTRIC	5,000 HRS	5,500	12 YRS	13 YRS	50%
085010	FORKLIFT, ENGINE DRIVEN, UP TO 3,999 LB CAPACITY	9,000 HRS	10,000	12 YRS	13 YRS	75%
085020	FORKLIFT, ENGINE DRIVEN, 4,000 LB AND OVER CAPACITY	9,000 HRS	10,000	12 YRS	13 YRS	75%
090010	GRADER, MOTOR, CLASS I, UP TO 109 H.P.	5,000 HRS	5,500	12 YRS	13 YRS	50%
090020	GRADER, MOTOR, CLASS II, 110-134 H.P.	6,000 HRS	6,500	13 YRS	14 YRS	75%
090030	GRADER, MOTOR, CLASS III, 135-149 H.P.	6,000 HRS	6,500	13YRS	14 YRS	75%
090040	GRADER, MOTOR, CLASS IV, 150 H.P. AND GREATER	6,000 HRS	6,500	12 YRS	13 YRS	100%
110010	LOADER, CRAWLER, UP TO 1.9 CU.YD. CAPACITY	**3,000 HRS**	**3,500**	13 YRS	14 YRS	**50%**
110020	LOADER, CRAWLER, 2 CU. YD. CAPACITY AND GREATER	**3,000 HRS**	**3,500**	13 YRS	14 YRS	**50%**
115000	LOADER, PNEUMATIC TIRED, SKID STEER	**2,000 HRS**	**2,500**	**9 YRS**	**10 YRS**	**50%**
115010	LOADER, PNEUMATIC TIRED, UP TO 1 1/2 CY	5,000 HRS	6,000	13 YRS	14 YRS	75%
115020	LOADER, PNEUMATIC TIRED, 1 1/2 CY	5,200 HRS	5,500	13 YRS	14 YRS	100%
115030	LOADER, PNEUMATIC TIRED, 2 CY	5,500 HRS	6,000	13 YRS	14 YRS	75%
115040	LOADER, PNEUMATIC TIRED, 2 1/2 AND 3 CY	6,500 HRS	7,000	13 YRS	14 YRS	100%
132040	MOWER, TRAIL TYPE, ROTARY, 9 FT AND GREATER	3,000 HRS	3,500	8 YRS	9 YRS	100%
136010	MOWER, SLOPE, SIDE BOOM, TRACTOR MOUNTED, INC TRACTOR	2,000 HRS	2,200	13 YRS	14 YRS	100%
140040	PAINT STRIPE MACHINE, 2 COLOR, MULTI-LINE, TRUCK MOUNTED	10,000 HRS	11,000	10 YRS	11 YRS	100%
154000	PAVEMENT PROFILING MACHINE, SELF PROPELLED	**6,000 HRS**	**7,000**	10 YRS	11 YRS	100%
156010	PAVER, BITUMINOUS, SELF PROPELLED	5,000 HRS	5,500	11 YRS	12 YRS	50%
162020	PULVERIZER-MIXER, EARTH, SELF PROPELLED	3,000 HRS	3,500	9 YRS	10 YRS	50%
170010	ROLLER, FLATWHEEL, SELF PROPELLED 4-6 TON W/PNMTC TRS	3,000 HRS	3,500	16 YRS	17 YRS	75%
170020	ROLLER, FLATWHEEL, SELF PROPELLED 5-8 TON	**4,000 HRS**	**4,500**	16 YRS	17 YRS	75%
170030	ROLLER, FLATWHEEL, SELF PROPELLED 8-14 TON	**4,000 HRS**	**4,500**	16 YRS	17 YRS	75%
174010	ROLLER, PNEUMATIC TIRED, SELF PROPELLED	**3,000 HRS**	**3,500**	14 YRS	15 YRS	100%
176010	ROLLER, TAMPING, SELF PROPELLED	3,000 HRS	3,200	15 YRS	16 YRS	50%
178010	ROLLER, VIBRATING, SELF PROPELLED	2,000 HRS	2,200	15 YRS	16 YRS	50%
178020	ROLLER, VIBRATING, SELF PROPELLED W/PNEUMATIC TIRES	2,500 HRS	2,800	12 YRS	13 YRS	50%
186000	SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED	6,000 HRS	6,500	12 YRS	13 YRS	100%
186010	SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED, SOLAR PWRED	6,000 HRS	6,500	12 YRS	13 YRS	100%
192010	SPRAYER, HERBICIDE/INSECTICIDE, TRUCK MOUNTED (INC TRK)	6,300 HRS	6,700	9 YRS	10 YRS	100%

194010	SPREADER, AGGREGATE, SELF POWERED	5,000 HRS	5,200	15 YRS	16 YRS	100%
202010	SWEEPER, ROAD, SELF PROPELLED	3,000 HRS	3,200	10 YRS	11 YRS	100%
204020	SWEEPER, STREET, TRUCK MOUNTED	5,000 HRS	5,500	8 YRS	9 YRS	75%
204030	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, UP TO 5.9 CY	5,000 HRS	5,500	8 YRS	9 YRS	**75%**
204040	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, 6 CY & UP	5,000 HRS	5,500	8 YRS	9 YRS	75%
214000	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, MILEAGE	140,000 MI	150,000	12 YRS	13 YRS	100%
214010	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, HOURLY	4,000 HRS	4,500	12 YRS	13 YRS	100%
220010	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) TO 100 HP	**4,000 HRS**	**4,500**	12 YRS	13 YRS	75%
220020	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 100-129 HP	6,000 HRS	6,500	12 YRS	13 YRS	75%
220030	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 130-179 HP	6,000 HRS	6,500	12 YRS	13 YRS	100%
230010	TRACTOR, PNEUMATIC TIRED, TO 49 HP (TRACTOR ONLY)	3,000 HRS	3,300	14 YRS	15 YRS	100%
230020	TRACTOR, PNEUMATIC TIRED, 50-64 HP (TRACTOR ONLY)	3,000 HRS	3,300	14 YRS	15 YRS	100%
230030	TRACTOR, PNEUMATIC TIRED, 65 HP & GREATER (TRACTOR ONLY)	3,000 HRS	3,500	14 YRS	15 YRS	100%
240020	TRACTOR, PNEUMATIC TIRED, W/LOADER & BACKHOE, TO 60 HP	3,500 HRS	3,700	14 YRS	15 YRS	75%
240030	TRACTOR, PNEUMATIC TIRED, W/LOADER AND BACKHOE, 60 HP & UP	6,000 HRS	7,000	**14 YRS**	**15 YRS**	**75%**
260010	TRAILER, EQUIPMENT, TILT BED/UTILITY, TO 24,000 LB CAPACITY	3,000 HRS	3,200	15 YRS	16 YRS	**200%**
260020	TRAILER, EQUIPMENT, TILT BED/UTILITY, 24,000 LB CAP & GREATER	4,000 HRS	4,500	15 YRS	16 YRS	**200%**
260030	TRAILER, EQUIPMENT, GOOSENECK	**9,000 HRS**	**10,000**	15 YRS	16 YRS	**200%**
280010	TRAILER, TRANSPORT, PLATFORM	4,000 HRS	4,500	12 YRS	13 YRS	100%
280020	TRAILER, TRANSPORT, SIGN	4,000 HRS	4,400	14 YRS	15 YRS	100%
400010	TRUCK, 4-WD UTILITY AND CARRYALL	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
400020	TRUCK, 4-WD PICKUP, ALL STYLES	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
400030	TRUCK, 2-WD UTILITY VEHICLE, 3961-5000 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
410010	TRUCK, CARRYALL, UP TO 6950 LB GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
410020	TRUCK, CARRYALL, 7000 LB GVWR AND GREATER	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
420010	TRUCK, CARGO OR WINDOW VAN, MINI, UP TO 6200 LB GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
420020	TRUCK, CARGO OR WINDOW VAN, FULL-SIZE, 6200 LB GVWR & UP	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430010	TRUCK, LIGHT DUTY, PICKUP, UP TO 4600 LB GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430020	TRUCK, LIGHT DUTY, PICKUP, 4600 - 6199 LB GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430030	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 4600-6199 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430040	TRUCK, HEAVY DUTY COMPACT, 4320-5600 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430050	TRUCK, EXTENDED CAB COMPACT, 4245-5034 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
430070	TRUCK, EXTENDED CAB 1/2 TON, 6000-6799 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
440010	TRUCK, LIGHT DUTY, PICKUP, 6200-7999 LB GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
440020	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 6200-7999 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
440030	TRUCK, EXTENDED CAB 3/4 TON, 6800-9000 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**

450010	TRUCK, LIGHT DUTY, 8000-8599 GVWR, PICKUP BODY	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
450020	TRUCK, LIGHT DUTY, 8000-8599 GVWR, OTHER BODY STYLES	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
460010	TRUCK, LIGHT DUTY, 8600-14999 GVWR, PICKUP BODY	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
460020	TRUCK, LIGHT DUTY, 8600-14999 GVWR, OTHER BODY STYLES	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
470020	TRUCK, LIGHT DUTY, CR CAB, 7901-8599 GVWR, OTHER BODY STYLES	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
470030	TRUCK, LIGHT DUTY, CR CAB, 8600-14999 GVWR, OTHER BODY STYLES	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
480010	TRUCK, PLTFM, PLTFM DUMP, STAKE, 8600-14999 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
490010	TRUCK, LIGHT/MEDIUM, 14,500 TO 18,999 GVWR	**110,000 MI**	**130,000**	**9 YRS**	**10 YRS**	**100%**
500010	TRUCK, ALL BODY STYLES, 15,000-18,900 GVWR	**130,000 MI**	**140,000**	**10 YRS**	**11 YRS**	**100%**
510010	TRUCK, ALL BODY STYLES, 19,000-20,900 GVWR	**130,000 MI**	**140,000**	**10 YRS**	**11 YRS**	**100%**
520010	TRUCK, ALL BODY STYLES EXC CONV DUMP, 21000-25400 GVWR	**130,000 MI**	**140,000**	**10 YRS**	**11 YRS**	**100%**
520020	TRUCK, CONVENTIONAL DUMP, 21000-25400 GVWR	**130,000 MI**	**140,000**	**10 YRS**	**11 YRS**	**100%**
520030	TRUCK, EJECTION TYPE MATERIAL BODY, 21000-25400 GVWR	**130,000 MI**	**140,000**	**10 YRS**	**11 YRS**	**100%**
530010	TRUCK, ALL BODY STYLES, EXC CONV DUMP/WRKR 25500-28900	**130,000 MI**	**140,000**	10 YRS	11 YRS	**100%**
530020	TRUCK, CONVENTIONAL DUMP, 25500-28900 GVWR	**130,000 MI**	**140,000**	10 YRS	11 YRS	**100%**
530030	TRUCK, EJECTION TYPE MATERIAL BODY, 25500-38900	120,000 MI	130,000	10 YRS	11 YRS	**100%**
540010	TRUCK, DUMP, SINGLE REAR AXLE,29000-42900 GVWR	140,000 MI	**150,000**	**16 YRS**	**17 YRS**	100%
540020	TRUCK, DUMP, TANDEM REAR AXLE, 43000 GVWR AND GREATER	**180,000 MI**	**200,000**	**16 YRS**	**17 YRS**	100%
550010	TRUCK, ALL STYLES EXC DUMP, SINGLE REAR AXLE 29000-38900	**140,000 MI**	**150,000**	**16 YRS**	**17 YRS**	**100%**
550020	TRUCK, ALL STYLES EXC DUMP, TANDEM REAR AXLE 39000 +	**140,000 MI**	**150,000**	**16 YRS**	**17 YRS**	**100%**
600010	TRUCK TRACTOR, SINGLE REAR AXLE, UP TO 60000 GCWR	**140,000 MI**	**150,000**	**16 YRS**	**17 YRS**	**100%**
600020	TRUCK TRACTOR, SINGLE REAR AXLE, 60000 GCWR & GREATER	**140,000 MI**	**150,000**	**16 YRS**	**17 YRS**	100%
600030	TRUCK TRACTOR, TANDEM REAR AXLE, ALL GCWR	200,000 MI	250,000	**16 YRS**	**17 YRS**	100%

ORIGINALLY, TERM LOOKED AT:

70 CLASS CODES OF THE 310 IN EOS-----------------------------22.58%

12,584 UNITS OF EQUIPMENT OF 17,357--------------------------72.51%

$251,709,530.54 OF THE ORIGINAL PURCHASE COST---------82.28%

*CURRENTLY, TERM LOOKS AT:

115 CLASS CODES OF THE 195 APPLICABLE IN EOS-----58.97%

14,159 UNITS OF EQUIPMENT OF 17,007--------------------83.25%

$573,446,644.36 OF THE ORIGINAL PURCHASE COST---84.09%

*BASED ON TERM AND R33B REPORTS, EXCLUDING CLASS CODES CONVERTED TO MES IN 2008

APPENDIX A.C: FAQS

A.C.1 - HOW TO CREATE A DESKTOP SHORTCUT?

To create a shortcut icon on the desktop, open the “dist” folder first, and then right-click the executable file “Optimizer.jar” and select the “Copy” option. Next, right-click anywhere on the desktop and select the “Paste shortcut” option. Now, there should be an icon entitled “Shortcut to Optimizer” on the desktop that allows the user to double click and execute the ERO software.

A.C.2 - CAN I COPY AND PASTE THE OPTIMIZER ANYWHERE AND EXECUTE THE FILE?

Not if the Optimizer is copied alone. However, if it is moved along with the “\lib” folder to the same location, or the Optimizer is pasted as a shortcut only, it will function properly. During the development of the GUI, a special file (i.e. miglayout executable) was used for the development convenience of the GUI and placed in the “\lib” folder. As a result, the “Optimizer.jar” should remain in the same folder as the “\lib” folder (i.e. the “Optimizer\dist” folder). If the Optimizer is copied to another location the “\lib” folder must also be copied to the same location (e.g. If the Optimizer is copied to the desktop, the “\lib” folder should also be copied to the desktop in order for the file to properly execute).

A.C.3 - IS JAVA SDK INSTALLATION REQUIRED?

No. The installation of Java SDK is not required to execute the ERO software. Java SDK is only required for the development of the ERO software.

A.C.4 - WHAT DOES THE MESSAGE “ERROR LOADING EQUIPMENT FILE FALSE” MEAN?

The newest version of Java Runtime Environment is not installed. Refer to section A.2.2 for information regarding the installation of Java Runtime Environment.

A.C.5 - HOW DO I ADD NEW DATA FOR EACH YEAR?

At the beginning of each fiscal year, the new TERM data from the past year should be input into the system in such a way that the software recognizes and can use the data (i.e. the 2009 TERM data format). The new TERM data must be input into the folder “\TERM Data\Input” (i.e., the Input Directory as discussed in section A.3.1.1) in the format “TERM_XXXX_Data” where the year is represented by XXXX (e.g. at September 1, 2011 - the beginning of the 2012 fiscal year, the 2011 data should be added in the form of “TERM_2011_Data”). Again, the user will be reminded to do so through a message displayed in a pop-up window right after the “Run” button is clicked. Again, the format of this input file should remain the same as the most recent TERM data (such as 2008 and 2009) provided by TxDOT during the development of this ERO solution software.

A.C.6 - WHAT IS KNAPSACK PROGRAMMING?

The knapsack problem is a problem in combinatorial optimization: Given a set of items, each with a weight and a value, determine the number of each item to include in a collection so that the total weight is less than or equal to a given limit and the total value is as large as possible. It derives its name from the problem faced by someone who is constrained by a fixed-size knapsack and must fill it with only the most useful items. In the ERO context, the size of the knapsack is determined by the annual budget and the set of items is the list of candidate equipment units for replacement. The cost of replacement is modeled as the weight of the items and the value of the items is represented as the cost savings of each replacement compared to the benchmark solution. The program maximizes the benefit of replacement compared to the benchmark decision and chooses the most optimal solution (i.e., an optimal list of equipment units for replacement) that fits the annual budget for the decision year.

Appendix B: Equipment Replacement Optimization: Part I. Solution Methodology, Statistical Data Analysis, and Cost Forecasting

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ABSTRACT: In this paper, we first conduct a comprehensive literature review of the state-of-the art and state-of-the practice of the equipment replacement optimization (ERO) problem. A comprehensive dynamic programming (DP) based optimization solution methodology is then

proposed and implemented to solving the ERO problem. The developed ERO software consists of three main components: 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 & forecasting; 2) A DP-based optimization engine that minimizes the total cost over a defined horizon; and 3) A Java based Graphical User Interface (GUI) that takes parameters selected by and inputs from users and coordinates the Optimization Engine and SAS Macro Data Cleaner and Analyzer. The first component (i.e., the SAS macro based Data Cleaner and Analyzer), is presented in detail. Preliminary numerical results of the SAS data analysis, estimation and forecasting of several costs are also discussed. Then in a following paper, the DP-based optimization engine and ERO software development (including the Java GUI) are presented in detail and comprehensive ERO numerical results are given.

Appendix C: Equipment Replacement Optimization: Part II. Dynamic Programming-Based Optimization

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ABSTRACT: The main purpose of this paper is to present a deterministic dynamic programming (DDP)-based optimization model formulation and propose both the Bellman and Wagner approaches to solving the equipment replacement optimization (ERO) problem. The developed solution methodology is very general and can be used to make optimal keep/replacement decisions for both brand-new and used vehicles both with and without annual

budget considerations. A simple numerical example is given to illustrate and step-through the Bellman DDP solution process and demonstrate how the DDP is used to solve the ERO problem via backward recursion. The developed DDP-based ERO software is tested and validated using the current Texas Department of Transportation (TxDOT) vehicle fleet data. Comprehensive numerical results, such as the software computational time and solution quality, are described and substantial cost-savings have been estimated by using this ERO software. Finally, future research directions are also suggested.

Appendix D: A Stochastic Dynamic Programming Approach for the Equipment Replacement Optimization with Probabilistic Vehicle Utilization

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ABSTRACT: In this paper, a stochastic dynamic programming (SDP) based optimization model is formulated for the equipment replacement optimization (ERO) problem that can explicitly account for the uncertainty in vehicle utilization. The Bellman's approach is developed and implemented to solving the ERO SDP problem. Particular attention is paid to the SDP state-space growth and special scenario reduction techniques are developed to resolve the "curse of dimensionality" issue that is inherent to the dynamic programming method to ensure that the computer memory and solution computational time required will not increase exponentially with the increase in time horizon. SDP software computer implementation techniques and functionalities are discussed. Comprehensive numerical results are described and future research directions are also suggested.