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16. Abstract

The TxDOT vehicle fleet is a fundamental part of the departmental infrastructure, enabling many activities essential to accomplishing the daily departmental operations. Maintenance of a robust vehicle fleet is essential but costly. On one hand, reductions in fleet costs are potentially beneficial to the department as a whole and thereby beneficial to the taxpayers of the State of Texas. On the other hand, not being able to respond adequately under disaster/emergency conditions is unacceptable and therefore maintaining a fleet robust enough to capably respond in a multi-event contingency is also critical.

TxDOT's new equipment replacement optimization software (TERM2) produced through project 0-6412 "Equipment Replacement Optimization" (ERO) by our research team can optimize the equipment retain/replace decision process, potentially resulting in substantial cost savings. Much of the current TERM2 research work and result findings can be seen from Fan et al. (2011a, 2011b).

The technical objectives of this project are to (1) Investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced; (2) Identify methods to estimate downtime costs coupled with TxDOT's current rightsizing efforts; (3) Review the use and development of advanced optimization techniques; (4) Recommend feasible ways to model the future uncertain purchase costs due to technology changes; (5) Review Texas's Emergency Management Strategy and support concept and list levels of commitment to the DEM and DPS; (6) Identify reasonable and likely simultaneous disaster/emergency event scenarios in Texas (if reasonably available, list equipment commitments for several historical simultaneous emergencies); (7) Review and describe how other state Departments of Transportation (DOTs) and major metropolitan governments provision their fleets to handle multiple disasters.

To accomplish this project, the research team has addressed the above issues and implemented in the TERM2 software and conducted a comprehensive review of the state of the art and state of the practice of equipment replacement/retention decisions based on future uncertain purchase costs, unavailability of funds, and disaster preparedness and a new TERM2 software has been developed with enhanced functionalities.

17. Key Word
Equipment Replacement, Retention Decision Making, Dynamic Programming, Texas Equipment Replacement Model (TERM), Statistical Analysis, Forecasting, Purchase Cost, Operating and Maintenance Cost, Salvage Value

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Products

This report also contains products 0-6693-P1 (*Robust Statistical Estimating and Forecasting Models used to Investigate the Future Uncertain Purchase Costs due to Technology Changes and the Down Time Costs coupled with TxDOT's Current Rightsizing Efforts*). Also provided to TxDOT as a result of this project was the developed software image files on a USB (P2).

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Chapter 1. Introduction

1.1 Problem Statement

The TxDOT vehicle fleet is a fundamental part of the departmental infrastructure, enabling many activities essential to accomplishing the daily departmental operations. Maintenance of a robust vehicle fleet is essential but costly. On one hand, reductions in fleet costs are potentially beneficial to the department as a whole and thereby beneficial to the taxpayers of the State of Texas. On the other hand, not being able to respond adequately under disaster/emergency conditions is unacceptable and therefore maintaining a fleet robust enough to capably respond in a multi-event contingency is also critical.

TxDOT currently owns and maintains an active vehicle fleet of approximately 17,000 units and annually replaces approximately 10% of its fleet. In monetary terms, TxDOT has a fleet valued at approximately $500,000,000, with an annual turnover of about $50,000,000. Any methodology that can improve TxDOT's replacement procedures can potentially save millions of dollars. TxDOT's new equipment replacement optimization software (TERM2) produced through project 0-6412 can optimize the equipment retain/replace decision process, potentially resulting in substantial cost savings. However, as future funding levels become more uncertain, non-availability of funds for vehicle replacement when optimally suggested by the software is very likely. If optimal timely replacement is impossible, then *what is the cost to the department of NOT replacing equipment when it should be replaced?* This question raises several implicit questions including these: how will downtime costs change as equipment ages and what are the potential impacts of future uncertain equipment purchase costs? It is expected that repair costs for fleet equipment get out of hand quickly as equipment ages and downtime cost may grow significantly as the fleet is downsized or "right-sized" because duplicate equipment items may not be available to fill the gap when critical items are down.

A related equipment replacement/retention issue is whether the fleet may inadvertently be reduced to a level that cannot support multiple simultaneous disasters and emergencies, which can include but are not limited to the following: 1. Natural disasters, e.g., hurricanes and flooding; 2. Major fire; 3. Terrorist attack; 4.Severe weather (snow, ice, fog). The increment of *equipment above and beyond the day-to-day "right size" quantities must be clearly established*. The department is currently conducting a second phase of equipment utilization review in an effort to properly "right size" the department's fleet. Both on-road and off-road fleet equipment needs are being reviewed for proper types of quantities and provisioning (location) throughout TxDOT's statewide operation. TxDOT's fleet currently consists of approximately 15,000 units: 3,000 unmotorized trailers, 9,000 on-road vehicles, and 3,000 off-road units. The TxDOT operational fleet has been reduced by over 1,000 units in recent years. The TxDOT fleet must support not only the mission and goals of the department by constructing and maintaining the state's highway system, but it also must support the state Department of Emergency Management (DEM) in times of disaster. TxDOT is considered a first responder in times of disaster, having the mission of going in to clear roadways ahead of emergency aid as well as assisting DEM with specialty equipment and manpower.

As described above, the significance of this project if evident. The results of this project could be implemented immediately as part of the new TERM2 equipment replacement optimization methodology and in TxDOT's current rightsizing efforts. Preliminary estimates of the savings likely achievable through TERM2 implementation are more than $1 million annually. The cost savings potentially available through implementation of results of this study could easily exceed those estimated for the TERM2 methodology. In addition, in any emergency situation, a certain degree of confusion and chaos occurs. The more organized and orderly TxDOT's response effort, the more likely that lives may be saved, property preserved, and evacuation accomplished. Because disasters or emergencies do not occur frequently, it is not desirable for TxDOT to wait until they happen to evaluate TxDOT's level of emergency preparedness and effectiveness. Implementation of results of this study can also potentially help TxDOT better organize and manage its fleet, and therefore be prepared and serve Texas residents should a disaster or emergencies occur.

1.1.1 Objectives

The goal of this project is to address the equipment replacement and retention decision making problem and provide robust optimal solutions to the questions as mentioned in Section 1.1 for TxDOT. To accomplish the goal, this research project entails the following specific objectives:

- Investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced;
- Identify methods to estimate downtime costs coupled with TxDOT's current rightsizing efforts;
- Review the use and development of advanced optimization techniques;
- Recommend feasible ways to model the future uncertain purchase costs due to technology changes;
- Review Texas's Emergency Management Strategy and support concept and list levels of commitment to the DEM and DPS;
- Identify reasonable and likely simultaneous disaster/emergency event scenarios in Texas (if reasonably available, list equipment commitments for several historical simultaneous emergencies);
- Review and describe how other state Departments of Transportation (DOTs) and major metropolitan governments provision their fleets to handle multiple disasters.

1.2 Expected Contributions

During this project, several advanced mathematical optimization algorithms as well as robust statistical estimating and forecasting models will be developed and all of these results will be implemented immediately as part of the new TERM2 equipment replacement optimization methodology and in TxDOT's rightsizing efforts. This will provide users the ability to use these advanced analytical tools to assess a variety of costs (purchase cost and down time cost) and impacts of being unable to execute optimal equipment keeps or replace decisions under different scenarios as well as other future uncertainties.

1.3 Report Overview

This remainder of the report will be organized as follows: Chapter 2 presents a comprehensive review of the state-of-the-art and state-of-the-practice literature on equipment replacement and equipment retention decision making. Chapter 3 investigates future uncertain purchase costs. Chapter 4 explores the costs of delaying replacing equipment. Chapter 5 presents a methodology for improving downtime, operations and maintenance (O&M) costs, and mileage forecasting. Chapter 6 describes a survey of fleet management practices during emergency situations and TxDOT's involvement in emergency situations. Chapter 7 presents the data analysis of fleet usage for TxDOT during multiple emergency events. Finally, Chapter 8 concludes this report with a summary and a discussion of the directions for future research.

Chapter 2. Literature Review

2.1 Introduction

This chapter will comprehensively review the state of the art and state of the practice on the following topics:

1. The use and development of advanced optimization techniques in the current TERM2 equipment replacement optimization as results of the TxDOT project 0-6412.
2. Specific concerns with the TERM2 program including how to determine the increase in cost when delaying purchases of equipment, what the potential impacts of future, uncertain equipment purchase costs will be, and how downtime costs will change as equipment ages.
3. Comprehensive review of the existing robust optimization methodology used for the critical primary and support equipment assets—quantities and placement problem, particularly in the fleet management and emergency management context.
4. Preliminary review of the Texas' Emergency Management Strategy and support concept and list levels of commitment to the DEM and DPS.
5. Preliminary review of how other state Departments of Transportation (DOTs) and major metropolitan governments provision their fleets to handle multiple disasters.

Topics 1 and 2 refer to Equipment Replacement Decision Making, which is discussed in Section 2.2, while topics 3, 4, and 5 are discussed in Section 2.3, Equipment Retention Decision Making.

2.2 Equipment Replacement Decision Making

2.2.1 Current TERM2 Status

TxDOT's new equipment replacement optimization software (TERM2) produced through project 0-6412 "Equipment Replacement Optimization" (ERO) by our research team, it can optimize the equipment retain or replace decision process and can potentially resulting in substantial cost savings. Much of the current TERM2 research work and result findings can be seen from Fan et al. (2011a, 2011b, 2012a, 2012b). The ERO problem deals with the determination of the replacement schedule so that the life cycle costs over the time horizon can be minimized. In other words, ERO determines the age at which to sell the asset so that costs (purchase cost plus operating & maintenance cost minus salvage value) are minimized over the defined horizon. Depending on the assumptions made under certain scenarios, the existing ERO problem can be classified into and solved by three categories from the solution approach perspectives: 1) Minimum equivalent annual cost (EAC) approach; 2) Experience/rule based (ERB) approach (e.g., TxDOT current replacement criteria); 3) Dynamic programming, which includes both deterministic dynamic programming (DDP) and stochastic dynamic programming (SDP). A comprehensive literature review of the state of the art and state of the practice (at many state DOTs and industries) of the ERO problem can also been seen from Fan et al. (2011a, 2011b, 2012a, 2012b).

In addition, the current TERM2 is developed and implemented using a comprehensive DP-based optimization solution methodology. It consists of three main components (Fan et al., 2011a): 1) A SAS macro based data cleaner and analyzer, which undertakes the tasks of raw data reading, cleaning, and analyzing, as well as cost estimation and forecasting; 2) A DP-based optimization engine that minimizes the total cost over a defined horizon; and 3) A Java-based graphical user interface (GUI) that takes parameters selected by users, displays the final results of the optimization, and coordinates the optimization engine and SAS macro data cleaner and analyzer. Figure 2.1 shows the flow chart of the solution methodology used in TERM2. These three components are briefly discussed as follows.

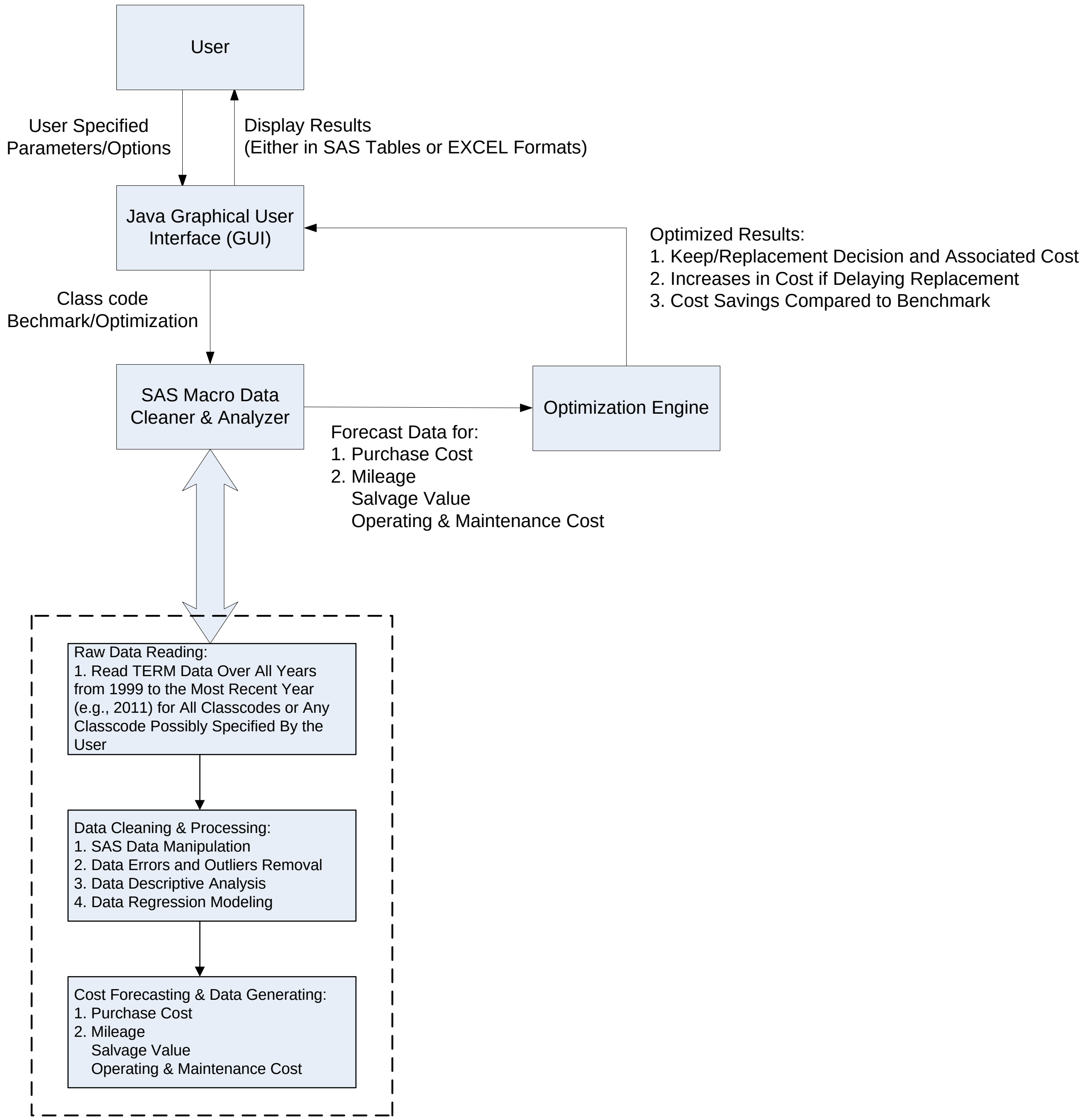
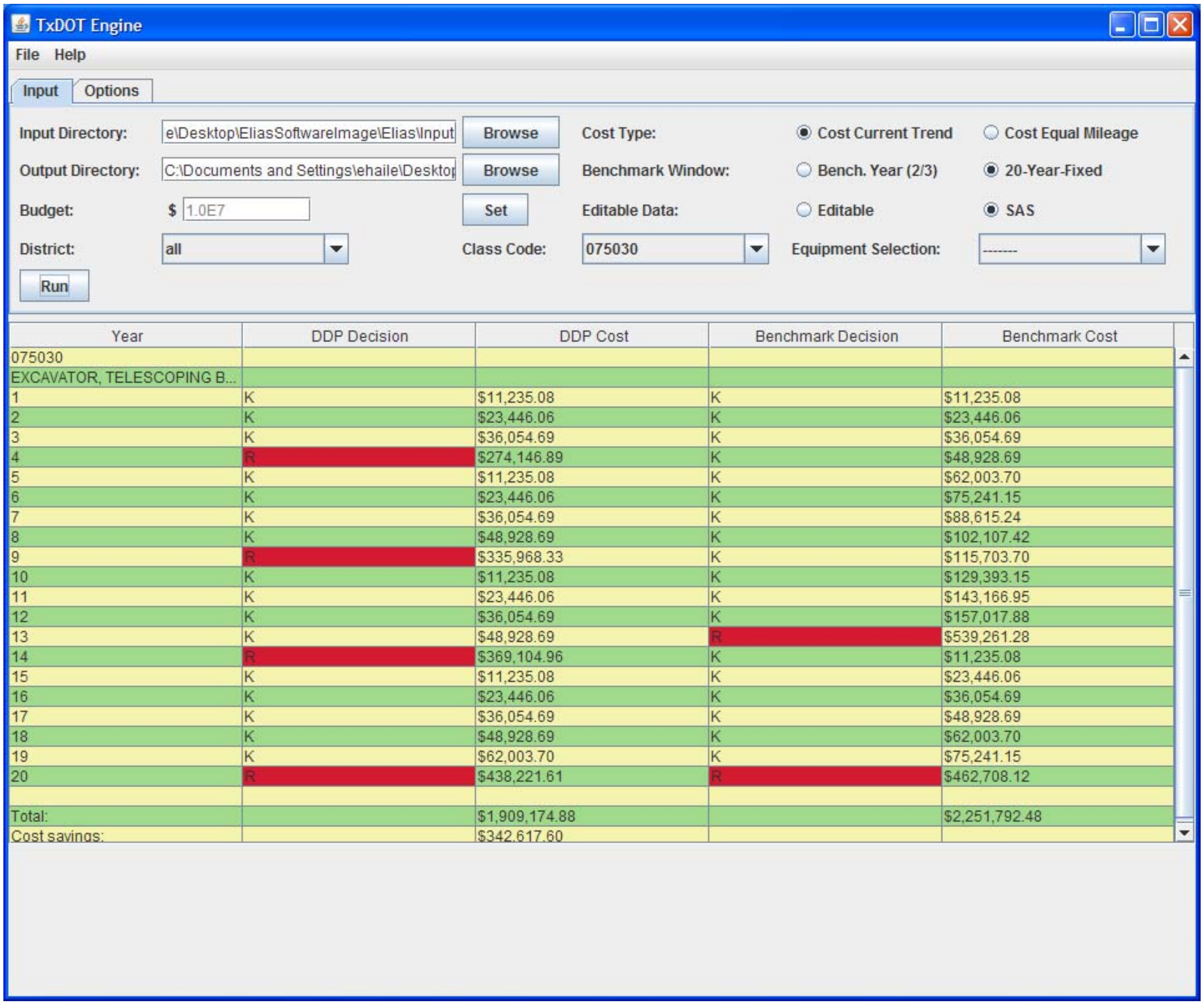


Figure 2.1 Flow Chart of the Solution Methodology Used in TERM2 (Adapted from Fan et al., 2011a)

2.2.2 Java GUI

As one can see from Figure 2.1, 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 screenshot of the Java GUI of TERM2 is presented below in Figure 2.2.



Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost
075030				
EXCAVATOR, TELESCOPING B...				
1	K	$11,235.08	K	$11,235.08
2	K	$23,446.06	K	$23,446.06
3	K	$36,054.69	K	$36,054.69
4	R	$274,146.89	K	$48,928.69
5	K	$11,235.08	K	$62,003.70
6	K	$23,446.06	K	$75,241.15
7	K	$36,054.69	K	$88,615.24
8	K	$48,928.69	K	$102,107.42
9	R	$335,968.33	K	$115,703.70
10	K	$11,235.08	K	$129,393.15
11	K	$23,446.06	K	$143,166.95
12	K	$36,054.69	K	$157,017.88
13	K	$48,928.69	R	$539,261.28
14	R	$369,104.96	K	$11,235.08
15	K	$11,235.08	K	$23,446.06
16	K	$23,446.06	K	$36,054.69
17	K	$36,054.69	K	$48,928.69
18	K	$48,928.69	K	$62,003.70
19	K	$62,003.70	K	$75,241.15
20	R	$438,221.61	R	$462,708.12
Total:		$1,909,174.88		$2,251,792.48
Cost savings:		$342,617.60		

Figure 2.2 A Screenshot of the Java GUI of TERM2 (Adopted from Fan et al. 2011a)

A detailed examination of the specific characteristics and functionalities of the Java GUI is also provided in Fan et al. (2011a).

2.2.3 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, then errors and outliers are removed, after the 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.

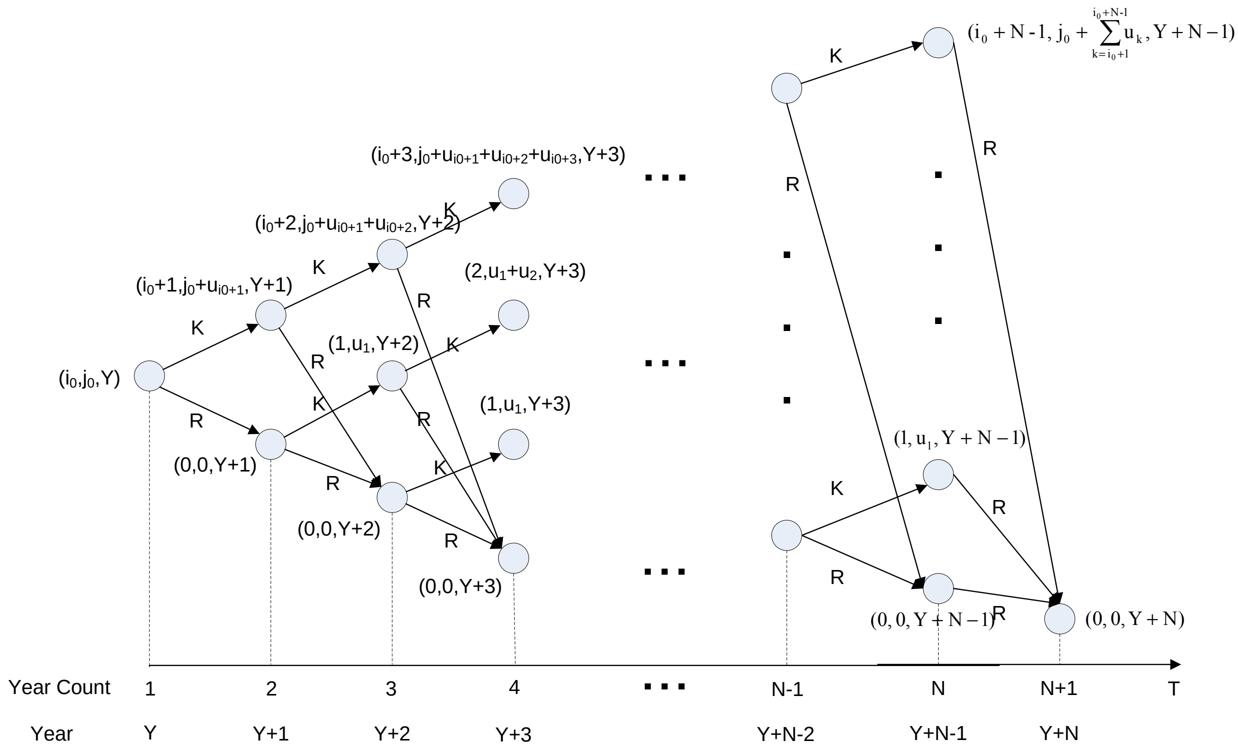
In particular, as part of the SAS macro data cleaner and analyzer, several advanced linear and nonlinear mathematical models (including five different types of models: linear model; polynomial model; logarithm model; exponential model; and power model) have been developed during the cost estimation and forecasting process in current TERM2. These include 1. the equipment purchase cost (vs. model year); 2. the annual O&M cost and the annual mileage (both vs. equipment age); 3. the salvage value (vs. model year and equipment age); and 4. the annual O&M cost per mile, also calculated using the equipment age as the only dependent variable. 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 terms of salvage value calculation, two high-quality exponential 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 in years as the independent variables for both heavy and light vehicle types. Further detailed information concerning the SAS Macro Data Cleaner and Analyzer and its data cleaning/analyzing procedures can be found in Fan et al. (2011a).

2.2.4 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.

Both DDP and SDP optimization models are formulated and the DP solution algorithms (including both Bellman's and Wagner's approaches) have been implemented and solved via backward recursion. The Java based DP solution software is developed to minimize the total costs for solving the ERO problem in TERM2. The DP-based ERO software has been tested and validated using current TxDOT vehicle fleet raw data (Fan et al., 2011a).

The Bellman's DDP and SDP approaches to solving the ERO problem are illustrated below in Figures 2.3 and 2.4 respectively. Detailed DDP and SDP model formulations and the advanced SDP scenario reduction techniques to circumvent the DP "curse of dimensionality" issue to solve the ERO problem can be found in Fan et al. (2011a).

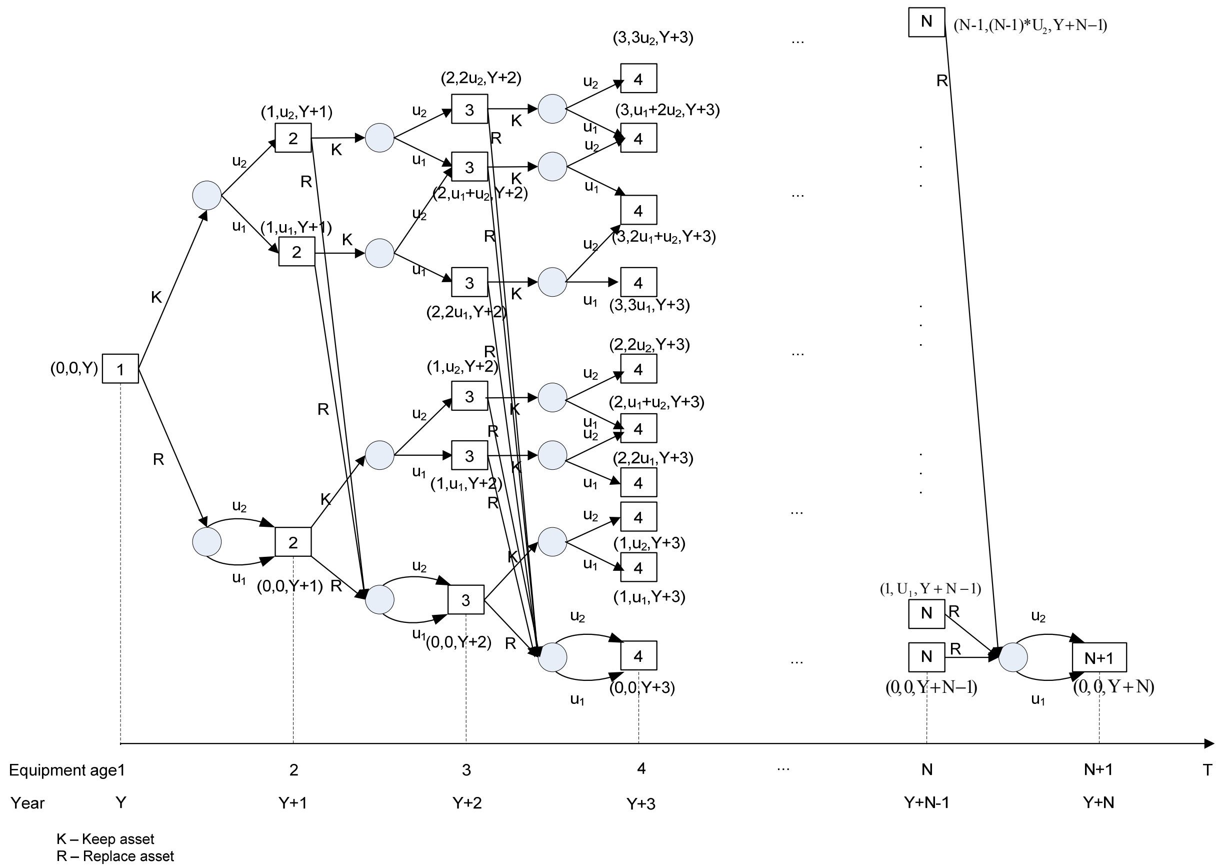


K – Keep asset
R – Replace asset
Note:

a. $(i_0 + N - 1, j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k, Y + N - 1)$ represents the status of a vehicle which is $(i_0 + N - 1)$-year old with its accumulative mileage being $(j_0 + \sum_{k=i_0+1}^{i_0+N-1} u_k)$ at the beginning of year $(Y + N - 1)$. u_k denotes the usage during the year at the end of which the equipment becomes k-year old. Similar notation follows.

b. The salvage value is associated with “R” decision. The decision is made at the beginning of each year where the starting node is located. The salvage value is referred to as the value of equipment age at the end of that year. The operating/ maintenance cost associated with “K” decision is related to the equipment age at the end of that year.

Figure 2.3 Bellman’s DDP Approach to Solving the ERO Problem (Adapted from Fan et al., 2011a)



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 2.4 SDP Formulation for the ERO Problem with Uncertainty in Asset Utilization: the 2-Level Case after Conducting the Scenario Reduction Treatment (Adapted from Fan et al., 2011a)

In summary, 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, a knapsack programming optimization method is 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 detailed in Fan et al. (2011a).

2.2.5 Software Development and Functionality

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. According to Fan et al. (2011a), much functionality has been included in the DP-based ERO software. Such functionalities include the following:

1) The user can choose to run optimization on either a single, specific classcode, or all classcodes for which there is available data.

2) The user can specify to run optimization for a specific equipment unit, for brand new equipment units, or for all equipment units.
3) The software allows the user to specify budget constraints.
4) Two different approaches for forecasting cost and usage data are available: Cost Current Trend and Cost Equal Mileage.
   a. "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.
   b. "Equal Utilization" —Takes the average mileage across all equipment with the 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.
5) 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.
6) The user can choose to run the software using SAS automatically generated cost data or use the Editable cost data and make any desired changes manually.
7) The software gives the option to conduct the cost calculation by either Inflation Rate of by Cost of Money.
8) The software allows users to selectively "Clean the data."
9) The user can choose from several different approaches, namely DDP, SDP 2-Level, or SDP 3-Level; and Bellman or Wagner.
10) The user can also choose to delay the replacement of equipment or replace it early by specifying a positive or negative delay time.
11) 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).
12) 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.

2.2.6 TERM2 Concerns

2.2.6.1 How to Determine the Increase in Cost when Delaying Purchasing Equipment?

In TERM2, our research team developed advanced DP-based optimization models and implementation software solutions for the equipment replacement software a result of project 0-6412. TERM2 now can optimize the equipment retain/replace decision process based on that class of equipment's age, mileage, salvage value, and the cost of replacement equipment, potentially resulting in substantial cost savings. However, TERM2 is currently developed without accounting for the uncertain annual budget constraints. As future funding levels become more uncertain, non-availability of funds for vehicle replacement when optimally suggested by the software is very likely. If optimal timely replacement is impossible, then what is the cost to the department of NOT replacing equipment when it should be replaced? In other words, how does one determine the increase in cost when delaying replacing equipment due to budget constraint? This question raises several implicit questions, including the following two that will be discussed below in Section 2.2.6.2 and 2.2.6.3 respectively.

2.2.6.2 What are the Potential Impacts of Future, Uncertain Equipment Purchase Costs?

TERM2 has shown some very interesting results. As results of the project 0-6412 (Fan et al., 2011a): as the 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 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 more unpredictable.

As mentioned before, the research team developed five different types of models (including linear/polynomial/logarithm/exponential/power models) in TERM2 as a result of project 0-6412 to investigate the impact of the purchase cost due to technology changes using model year as the independent variable. Although the models seem to perform well from the technical perspective, the purchase cost forecasts do not always yield intuitively desirable results. For some classcodes, even the best forecasting model may yield negative forecasting results for the purchase cost due to the economic recessions that occurred in the middle years of these TERM data sets or under some other rare circumstances (Fan et al., 2011a). How to further investigate and better model the future uncertain purchase costs due to technology changes and what are the potential impacts of future uncertain equipment purchase costs? It is anticipated that this project should result in developing alternative advanced statistical models and recommending feasible ways to model the future uncertain purchase costs.

2.2.6.3 How will Downtime Costs Change as Equipment Ages?

TERM2 has shown some very interesting results related to this topic. The results of the project 0-6412 (Fan et al, 2011a): 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 committed hours decrease noticeably. In particular, the adjusted total O&M cost increases initially and then decreases as equipment ages. The downtime 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 fuel-efficient and the risk of equipment being down generally increases. As a result, the adjusted total O&M cost increases initially and the downtime 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 dominate and therefore the adjusted total O&M cost will begin to decrease. The same logic applies to the downtime. The decrease in equipment utilization forces the downtime to begin to decrease after a certain point.

In particular, all cost data forecasting attempts are extremely important and can have a truly significant impact on the ERO retain/replace decision because they are used at each stage and are associated with each replace/keep decision (Fan et al., 2011a). It is expected that repair costs for fleet equipment get out of hand quickly as equipment is used longer and downtime cost may grow significantly as the fleet is downsized or "right sized" because duplicate equipment items may not be available to fill the gap when critical items are down. It is anticipated that this project should result in developing alternative advanced statistical models and recommending feasible ways to model how downtime costs will change as equipment ages coupled with the TxDOT's current ongoing right-sizing efforts.

2.3 Equipment Retention Decision Making

The preliminary review of the existing literature related to this topic can be classified into three categories (sub-topics):

1. Existing research on the use and development of advanced optimization techniques to solve the optimal fleet vehicle allocation and facility location problems, particularly under disaster/emergency event scenarios. In other words, this subtopic refers to the comprehensive review on the existing robust optimization methodology used in the optimal critical primary and support equipment assets—quantities and placement (i.e., the questions of "how many vehicles" and "where to place") problem, particularly in the fleet management and emergency management context.
2. Preliminary review of the Texas' Emergency Management Strategy, support concept, levels of commitment to the DEM and DPS.
3. Preliminary review of the state of the practice related to the emergence/disasters and how other state Departments of Transportation (DOTs) and major metropolitan governments provision their fleets to handle multiple disasters. The following subsections will present a comprehensive review of the existing literature on the state of the art/practice related to these three sub-topics.

2.3.1 Review of the Existing Research on the Optimal Fleet Vehicle Allocation and Facility Location Problems

As mentioned before, the TxDOT fleet must support not only the mission and goals of the Department by constructing and maintaining the state's highway system, but it also must support the state Department of Emergency Management (DEM) in times of disaster. In that effect, TxDOT must develop robust and optimized solutions to the question, "how does one determine "robust" alternatives for critical primary and support equipment assets—quantities and placement?" There has been a significant amount of research related to the optimization problem of how to allocate critical primary and support equipment assets (both quantities and placement). A few most recent and relevant research efforts are discussed below.

Fan and Machemehl (2007) investigated the dynamic vehicle allocation decision-making problem for vehicle fleet management in both time and space to maximize profits for the rental car service operator. A multistage stochastic linear integer model with recourse is formulated and a stochastic optimization method based on Monte Carlo sampling is proposed to solve this dynamic vehicle allocation problem. Fan et al. (2008) developed a stochastic optimization model for the dynamic vehicle allocation problem but this time in a carsharing context and solved the problem using a simulation-based stochastic optimization approach with recourse.

Lei et al. (2009) studied the optimal deployment of limited emergency response service (ERS) units in a metropolitan area, which is of typical interest to public agencies. A mixed integer set covering the optimization model was formulated to allocate different types of ERS units among their candidate base stations. The objective is to maximize the weighted total coverage of critical infrastructures (i.e., important facilities such as bridges, tunnels, interchanges, and transit terminals within the city's transportation network) in different time periods of a day. The constraints considered include the capacities of the base stations, service time reliability/standards to reach the critical infrastructures, and the available ERS fleet size (when there are many demands competing for services). Note that the model developed in this paper can explicitly take into account both spatial and temporal fluctuations of service demands and traffic congestion.

Yang et al. (2003) presented an integrated approach for the emergency medical service (EMS) location and assignment problem. They note that the EMS depot location problem as a strategic problem and the fleet assignment problem as a tactical one. It can be usually solved separately under some simplified assumptions. This paper made significant contributions by solving these two problems simultaneously in order to seek potential savings in both the average response times and the capital and operating costs. A simulation based genetic algorithm (GA) model was developed to solve this combined problem. The model accounts for emergency types, their response priorities, and whether or not they require dispatching of multiple units. The average response time and the capital and operating costs are used as criteria for evaluation. The GA model was tested with a real network and the results indicated that very good quality solutions can be produced.

Sathe and Miller-Hooks (2005) optimized the location and relocation decisions for a fixed fleet of response units in guarding critical facilities, using a mixed integer linear program with multiple objectives (to maximize secondary coverage and minimize cost). A genetic algorithm was developed to solve the model.

Huang et al. (2007) developed a mixed integer linear programming model to optimize the problem of allocating limited emergency service vehicles including fire engines, fire trucks, and ambulances among a set of candidate stations in which the objective is to maximize the service coverage of critical transportation infrastructure. A case study using data from the practice in Singapore was used to demonstrate the applicability of the proposed methodologies to a high-density metropolitan area.

In summary, Table 2.1 shows some examples of facility location problems using different modeling methods.

Table 2.1 Examples of Facility Location Problems Using Different Modeling Methods (Adopted from Huang et.al. 2007)

Type	Objective	Constraints	Examples
Covering problem	Maximize Coverage of demands [5-7]	• Given acceptable service distance/time; • Limited resource	• Locate EMS vehicles [8-10]; • Locate rural health care workers [11]; • Place a fixed number of engine and truck companies [12-13]
	Set covering: minimize the cost of facility location [14-15] :	• Specified level of coverage obtained; • Given acceptable service distance/time	Identify EMS vehicles locations [16-17]
P-Median problem	Minimize the total travel distance/ time between demands and facilities [18]	• Full coverage obtained • Limited resource	• Ambulance position for campus emergency service [19]; • Locate fire stations for emergency services in Barcelona [20]
P-Center problem	Minimize the maximum distance between any demand and its nearest facility	• Full coverage obtained ; • Limited resource	Locate EMS vehicles with reliability requirement [21]

In all, regarding the solution approach to one of the most important technical objectives of this project, i.e., "recommend 'robust' alternatives for critical primary and support equipment assets' quantities and placement," the review of the literature clearly reveals that this is a variant of the facility location optimization problem, which can and should be formulated as a mixed integer programming model (see Hillier and Lieberman, 2005). The solution methodology can include, but is not limited to, the traditional branch and bound method or some metaheuristic-based approaches (such as genetic algorithms) in case of an extremely large scale problem (Nemhauser and Wolsey, 1999). Also, robust optimization that can develop an optimal solution to account for the worst-case scenarios, and stochastic optimization with recourse, as well as some simulation-based optimization techniques, can also be considered. Our research team is very confident that appropriate, efficient, effective and algorithms can or will be developed and solved as this project moves along.

2.3.2 Review of the Texas' Emergency Management Strategy and Support Concept and List Levels of Commitment to the DEM and DPS

A report entitled "Disaster Response and Recovery Resource for Transit Agencies" (2006) was developed by FTA based on lessons learned from Hurricane Katrina and other events. It provided local transit agencies and transportation providers with useful information and best practices in emergency preparedness and disaster response and recovery. It explicitly discussed the role of federal agencies and states in disaster response by presenting an overview of available federal resources in support of emergency preparedness, disaster response, and disaster recovery, and the basic frameworks of the National Response Plan, the National Incident Management System, and State Emergency Management Plans.

Rick Perry (2004), the Governor of the State of Texas, presented the Texas Homeland Security Strategic Plan Part III State of Texas Emergency Management Plan in 2004. In this plan, the state disaster district boundaries are given on Page 5-1. In addition, TxDOT is defined as the PRIMARY agency for Public Works and Engineering; and the SUPPORT agency for

Communications, Evacuation, Firefighting, Public Information, Recovery, Direction and Control, Hazard Mitigation, Hazardous Materials and Oil Spill Response, Transportation, and Terrorist Incident Response on page 9-28 of this plan.

A detailed review of the state of the practice related to the emergency management plans and levels of commitment for TxDOT will be further described in Chapter 6.

2.3.3 Review of the State of the Practice Related to the Emergency/Disasters at other State Departments of Transportation (DOTs) and Major Metropolitan Governments

Effective coordination among the highway transportation and emergency services agencies is extremely important in order to improve all-hazards emergency management, enhance highway operations, and ensure homeland security. Shepherd et al. (2006) conducted research to identify and evaluate the underlying obstacles and opportunities for improving coordination among these groups. Institutional, operational, technological, and financial factors were taken into account. A survey administered to transportation and emergency services professionals in five states was conducted and analyzed. Short term improvement of emergency transportation operations were given as a result.

Nakanishi et al. (2003) assessed emergency preparedness of transit agencies with a focus on performance indicators. As they also stated in the paper, in any emergency situation, a certain degree of confusion and chaos occurs. The more organized and orderly the response effort, the more likely that lives may be saved and property preserved. Because emergencies do not occur frequently, it is unadvisable to wait until they happen to evaluate a transit agency's level of emergency preparedness. Instead, this paper developed the performance indicators that measure the achievement of emergency preparedness goals and policies of a transit agency.

Hanson (1999) conducted a case study of determining the right size of a rental vehicle fleet for the Virginia Department of Transportation's Division of Fleet Management (DFM) where the private-sector vehicle-rental contract enabled DFM to reduce the size of the trip pool because excess demand could be met with private-sector vehicles and cost savings were possible. Numerical results developed in this paper also showed that the DFM's contract with a private-sector company to provide rental vehicles as needed could reduce the overall cost of state employee travel to Virginia by approximately $20,000 per year.

In addition to scheduled maintenance projects, the North Carolina DOT stages back-up equipment throughout the state for emergency situations such as debris and snow removal after significant storms and to respond to unexpected road failures due to accidents or natural disasters (Wood 2010). The North Carolina DOT's equipment use during emergency conditions (nights and weekends) is included in the actual use but does not increase the total available time (Wood 2010).

A detailed review of the state of the practice related to the emergency/disasters at other state DOTs and major metropolitan governments will be further described in Chapter 6.

2.4 Summary

The information presented in this chapter has been presented in the above three sections: 1. Introduction; 2. Equipment Replacement Decision Making; 3. Equipment Retention Decision Making. This literature review of the state of the art and state of the practice related to this project has been comprehensively documented and this background information will serve the research team as a very useful reference for further research development.

Chapter 3. Investigating Future Uncertain Purchase Costs

3.1 Introduction

The original strategy for forecasting the purchase cost was developed for project 0-6412 (Fan et. al. 2011a, 2011b). This involved development of multiple statistical models to forecast equipment purchase costs. Upon implementation of the above strategy, some forecasted purchase costs were found to be much lower than expected, and in some extreme cases, negative. This prompted the research team to undergo a full review of the purchase cost forecasts for each classcode. It was discovered that the issue of decreasing forecasted purchase costs was fairly extensive due in large part to lower purchase cost values in the data near the end of the recorded period. This finding led to the development of a strategy intended to prevent the software from utilizing decreasing purchase cost forecasts. The obstacles discovered using the original approach, as well as the development of an alternate strategy and its subsequent implementation into the software package, are further described in the following sections.

Sensitivity analysis is also conducted to investigate the impacts of future uncertain equipment purchase costs on equipment replacement decision based on the further testing of the ERO software and result analyses. The impact of inflation rate on the optimal equipment replacement age, total cost, and cost savings is also updated and presented in Section 3.3.4.

3.2 Original Forecasting Model

The strategy for forecasting the purchase cost developed for project 0-6412 depended on the use of SAS, as initiated by the graphical user interface (GUI), to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast equipment purchase cost versus model year. In particular, the SAS macro source codes were developed for the following five different types of models: 1) Linear Model; 2) Polynomial Model; 3) Logarithm Model; 4) Exponential Model; and 5) Power Model.

The SAS macro also had the capability of running through all of the linear and nonlinear models and automatically identifying and selecting the best-fit model, per the highest R-square value, for forecasting the equipment purchase cost (using model year) for any chosen classcode. The objective was to use SAS to create and select the best-fit model for the data and incorporate that model for forecasting purchase cost into the optimization engine. For more information about the development of these models and the selection process, see Fan et al. (2011a, 2011b).

Through the evaluation of early versions of the software, it was discovered that purchase cost forecasts for a number of classcodes were unduly influencing the keep or replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that yielded decreasing, and in some cases negative, purchase costs for future years. The evaluation of the quality of the fit (R-square value) for the model options led to the software program choosing non-linear models for many of the equipment classcodes. Due to the distribution of data for some of these equipment types, this resulted in a curvilinear model with a negative slope generated over the years near the end of the recorded history of purchase costs, as illustrated in Figure 3.1.

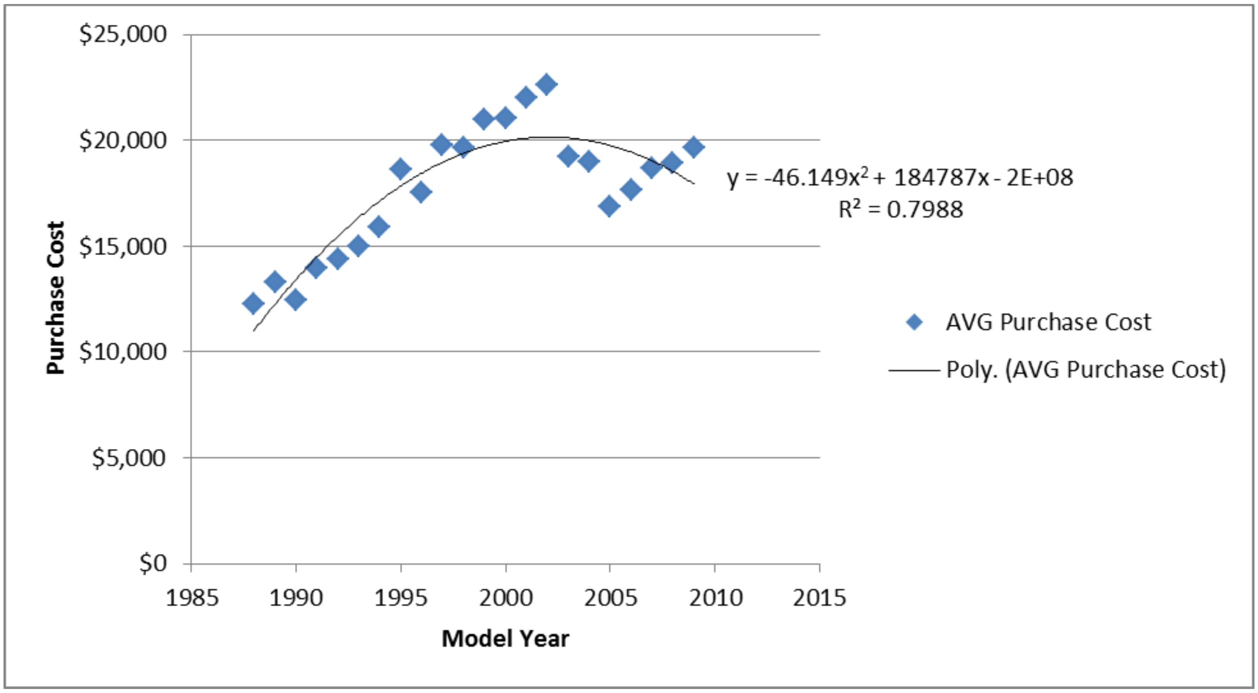


Figure 3.1 Graph of the Average Purchase Cost Versus Model Year with Best-fit Model for Classcode 430070 (Light Duty Truck)

Note that Figure 3.1 shows the nonlinear model yielding a good fit for the data (R-square value of 0.7988); however, the slope of the model is negative at the end of the existing time period and would subsequently result in a decreasing forecasted purchase cost for future years. Therefore, the software using models like this one resulted in purchase costs being forecasted to decrease each year of the time horizon (20 years). It was determined that this would have a detrimental impact on the ability of the optimization engine to appropriately generate recommendations for replacing equipment, as the long-term decreasing trend is counterintuitive. As such, several methods of troubleshooting the problem were identified and tested.

3.3 Development and Implementation of an Alternate Strategy

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

3.3.1 Testing Alternate Strategies

The use of a factor based on the inflation rate, in order to increase the forecasted purchase cost by a given percentage based on the last year of data available, was tested first. While this method solved the issue of a decreasing forecasted purchase cost, it did not take into account the historical purchase cost data beyond the last year recorded. It was determined that this would not be a universally effective method for forecasting purchase costs as it does not always effectively demonstrate the overall trend of the data. However, it was designated as an alternative if the other methods failed to yield better results. One of those options was including supplemental explanatory variables, in addition to model year, in the forecasting model.

The variables chosen for testing included MSRP, Consumer Price Index (CPI), and Producer Price Index (PPI). These values were readily attainable for including in the model; however, an evaluation of a multitude of variable combinations did not produce a robust solution. The MSRP was initially designated for replacing the purchase cost data in the model. It was anticipated that using the MSRP as a response variable with model year as the predictor would result in a more stable model. While the MSRP model was found to demonstrate a smoother trend, with a less pronounced tendency toward decreasing purchase prices than the historical purchase cost information, a negative slope still developed in the long-term forecast (20 years). Using MSRP in place of the actual purchase cost data yielded improved results, but it didn't solve the underlying issue; therefore, several alternatives utilizing consumer and producer price indices were evaluated.

The alternatives tested included adding the price indices to the models with either historical purchase cost or MSRP as the response variable. The overall CPI was tested, as well as the CPI for trucks, both trucks and automobiles, and new vehicles only (excluding used vehicle purchases). The PPI for automobiles, light trucks, and utility vehicles was also assessed. While inclusion of the price indices was shown to improve short-term forecasts of purchase price (approximately 5 years), it did not yield satisfactory results for longer term forecasts. Forecasted prices were shown to far exceed expected trends for purchase costs over a 20-year horizon. Therefore, additional options were developed for investigation.

The option of using moving averages to dampen the effect of the negative trend for the purchase cost was also evaluated. The use of two-year, three-year, and four-year moving averages was attempted. It was determined that using a moving average resulted in a flattening of the purchase cost curve, but the model repeatedly failed to demonstrate the ability to forecast a purchase price that was not inhibited by a negative slope. Again, the fundamental problem remained. It was decided to further evaluate the additional models created by the statistical analysis software from the original data, other than the one chosen by the software as the best fit.

Although the other models did not demonstrate the best overall fit, they were investigated for their ability to project an increasing purchase cost in the future. It was discovered that many of the polynomial, logarithm, exponential, and power models developed by the statistical analysis software produced a good fit for the data; however, the vast majority resulted in projecting a decreasing purchase cost or otherwise counter-intuitive projection of purchase cost. In the end, it was determined that the simple linear model provided a reasonably good fit for the data while projecting an increasing purchase cost in the future. The linear model was therefore chosen as the best model for projecting the purchase cost for the light duty truck, classcode 430070.

Per the results for the light duty truck, a linear model was subsequently developed for all of the classcodes in the database. Overall, the data and subsequent models for 125 classcodes were evaluated. In some cases, troubleshooting was required to improve the fit of the models. This involved investigating the data for outliers or model year price information influenced by relatively few entries. In these cases, the data were cleaned to yield better results. The data for some similar classcodes were combined to improve the results for codes where relatively small, individual sample sizes were available for the model's development.

This process resulted in a series of models based on the existing data that could be used to forecast more dependable purchase cost trends. In addition, the simplified approach enables the more stable linear model to be efficiently updated given additional purchase cost data obtained in the future, without the risk of an extensive alteration to the model formula. While this process appeared to yield a relatively robust solution to the aforementioned problem of decreasing forecasted purchase costs, it involved the creation of appropriate linear models manually. Therefore, a variation of this strategy was devised for implementation that could be automatically duplicated by the software via an algorithm.

3.3.2 Developing a Software Algorithm

To determine whether an automated process could be implemented to create and evaluate linear models for forecasting purchase costs, a series of test runs were completed to develop an algorithm. These tests were carried out in Excel and involved the manual evaluation of 75 classcodes. Each classcode was evaluated by determining if a linear model, created from the historical TERM data, met thresholds for sample size, goodness of fit, and slope. The thresholds were established as follows: sample size greater than 6 entries (or years for which purchase cost data exists within the last 20), R-square value greater than 0.60, and slope of the linear model greater than 0. The intent was for a linear model that passes all three checks to be chosen to forecast the purchase cost in the software. It was determined that a linear model would be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of application in an algorithm, and its provision of a relatively good fit overall for any data trends. It was discovered for the non-inflation rate adjusted purchase cost data that a linear model captured the historical trends quite well. However, it should be noted that the inflation adjusted purchase cost was ultimately utilized for the forecasting strategy. Figure 3.2, below, illustrates an example where this strategy would be utilized for forecasting purchase cost, i.e., the linear model created passes all three of the thresholds.

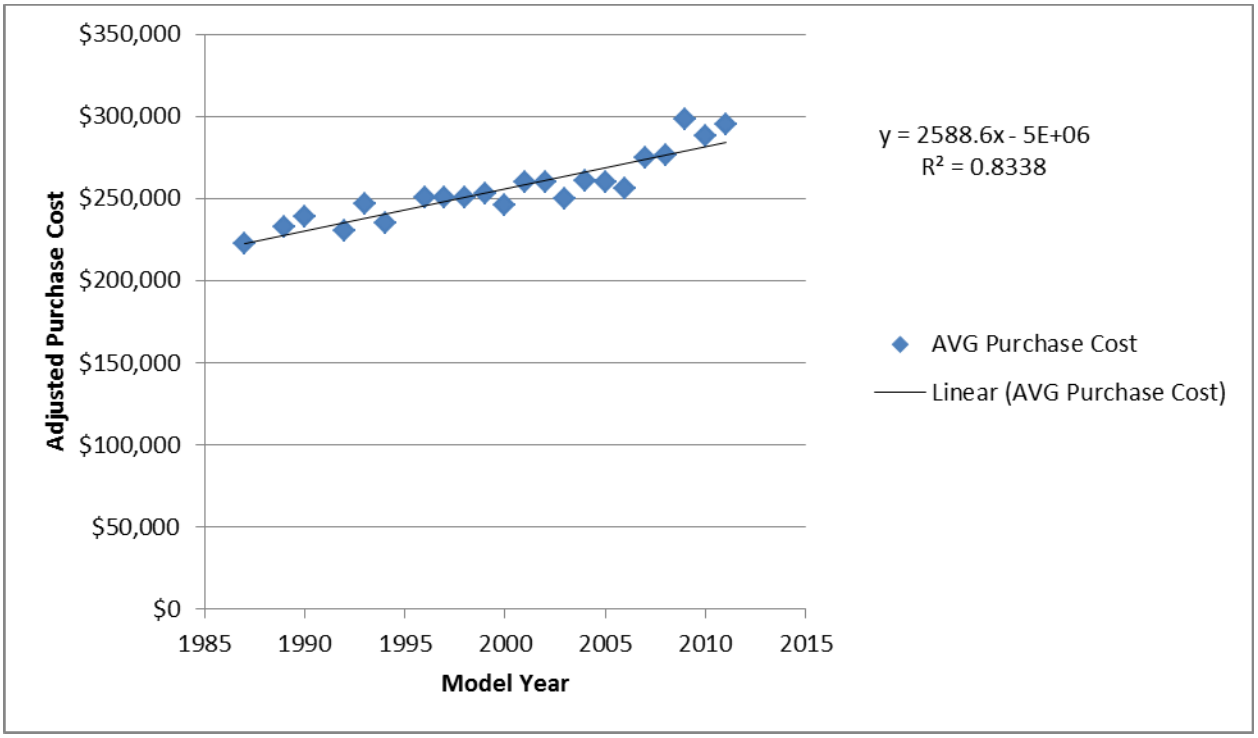


Figure 3.2 Graph of the Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 75010 (Excavator, Telescoping Boom, Carrier Mounted)

If any of the aforementioned thresholds are not met by the created model, then a default option is to be utilized. The purpose of this strategy is to provide a fail-safe to ensure that an increasing purchase cost is always forecasted. The default option for forecasting the purchase cost was chosen to be a formula where one-half of the inflation rate (inflation rate currently input as 3.2649%) is multiplied by the current year's purchase cost to establish the value for the subsequent year. Specifically, the purchase cost for each future year is based on the previous year's adjusted purchase cost multiplied by one plus one-half of the inflation rate (1.0163245). This strategy was chosen based on input from prior meetings with TxDOT personnel where it was suggested that the inflation rate be used as a multiplier in order to guarantee an increasing purchase cost is forecasted.

It should be noted that one-half of the inflation rate was chosen since the values input into the model for purchase cost are those already adjusted to account for inflation, i.e., the one-half inflation rate multiplier is to account for an annual increase in purchase cost beyond inflation. This results in a gradual increase in adjusted purchase cost that subtly accounts for uncertainties involved in predicting future changes. Furthermore, use of the inflation adjusted purchase cost data helped to ensure appropriate values for the forecasted purchase cost were input into the optimization engine, as well as to guarantee that no further adjustments would be made to the values after the forecasting process that might otherwise result in failing the threshold tests. Below, Figure 3.3 illustrates an example where the linear model created for the adjusted purchase cost failed the threshold test for goodness of fit and the inflation rate adjustment would be utilized as the forecasting method.

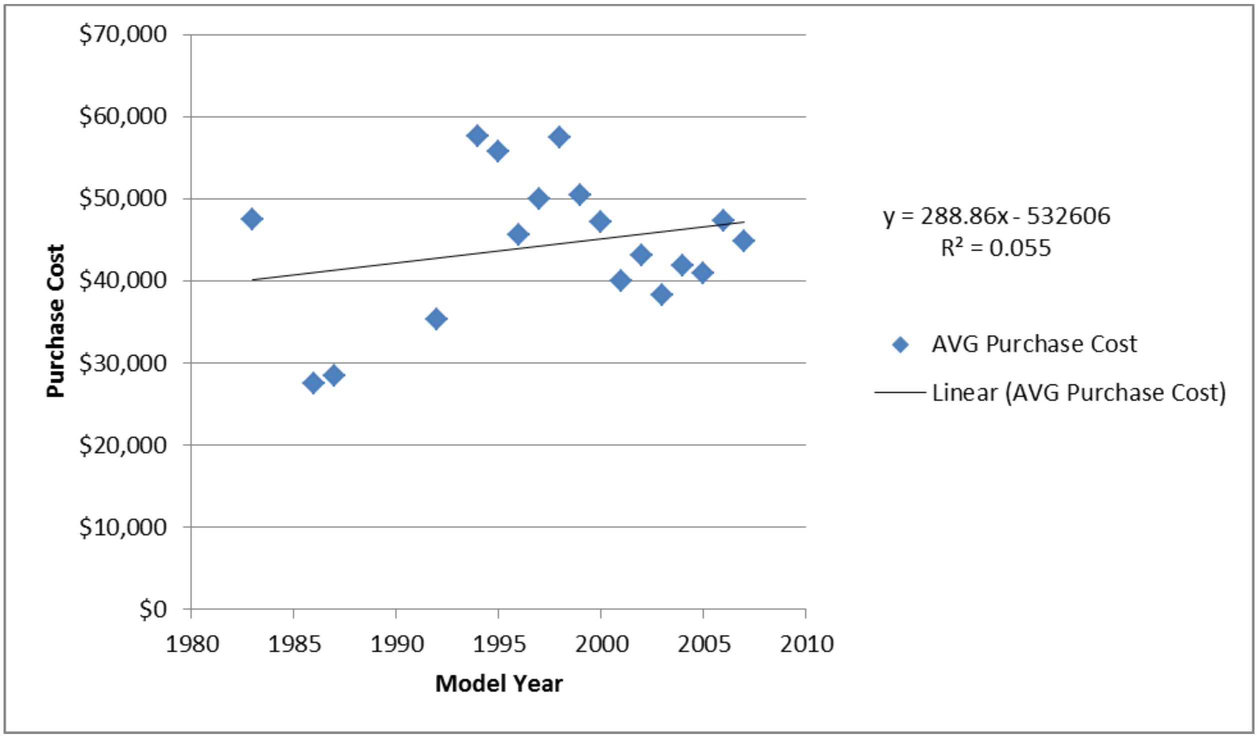


Figure 3.3 Graph of the Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 115000 (Loader, Pneumatic Tired, Skid Steer)

Before finalizing the algorithm for implementation into the software, a check was initiated to ensure the data sets used to create the linear models were thoroughly evaluated. In addition to the SAS macro based data cleaning process, another outlier removal procedure was implemented as part of the algorithm to eliminate major outliers from the data before the linear models are created by the software. To see more information about the SAS macro based data cleaning process involving the first outlier treatment, see Fan et al. (2011b). In the second round of the outlier removal process, upper and lower thresholds are created for a range of acceptable values. Those thresholds are calculated based on the lower and upper quartiles (Q_1 and Q_3) and the subsequent interquartile range ($IQR = Q_3 - Q_1$) as follows:

$$F_1 \ (lower\ threshold) = Q_1 - [2 * 1.5 * (Q_3 - Q_1)]$$
$$F_3 \ (upper\ threshold) = Q_3 + [2 * 1.5 * (Q_3 - Q_1)]$$

As such, adjusted purchase cost values falling outside of the above thresholds are eliminated from consideration for the creation of the linear models. With the outlier removal process and the three threshold tests determined, along with the primary and secondary (default) forecasting options established, the details for the algorithm were finalized. The algorithm was now ready to move from the conceptual stage to implementation in the software.

3.3.3 Implementing the Algorithm

The implementation process for the aforementioned software algorithm, as developed using SAS macro codes, is provided in Figure 3.4.

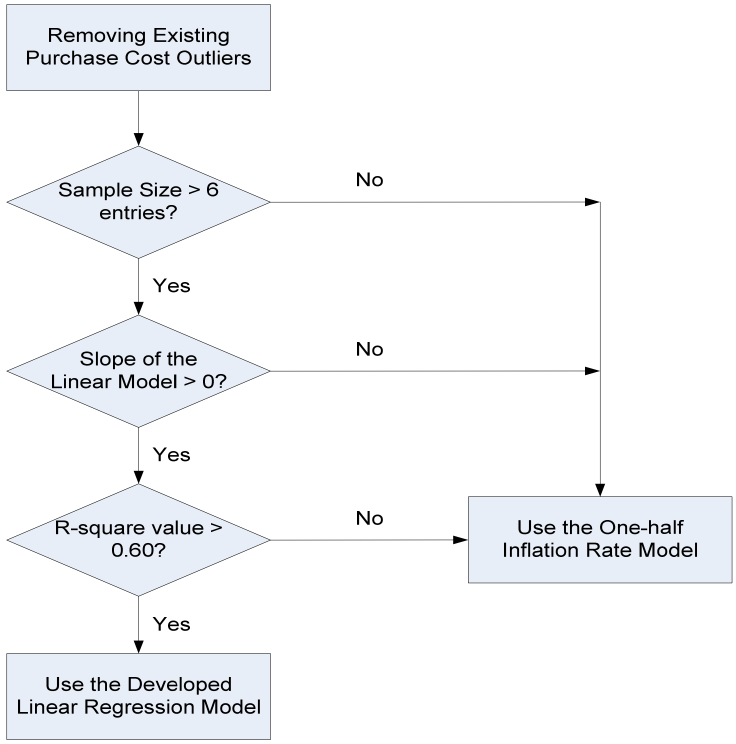


Figure 3.4 Flow Chart of the Purchase Cost Forecasting Algorithm Software Implementation

As shown in Figure 3.4, the algorithm first removes the remaining outliers for the purchase cost across all model years using the aforementioned IQR method, as described in Section 3.3.2. Then, it checks the following three conditions: whether or not the sample size (i.e., the data entries for average purchase cost) is greater than 6; whether or not the slope of the linear model is positive; and whether or not the R-square value is great than 0.6. If any of these three condition check fail, then the software will use the one-half inflation rate model to conduct the future purchase cost forecast. On the other hand, if all three condition check pass, the software will use the developed linear regression model.

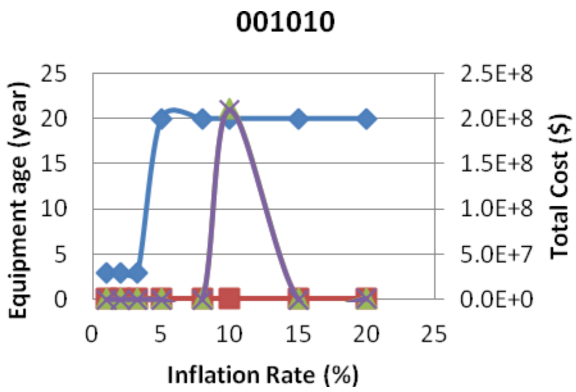
3.3.4 Reviewing Results

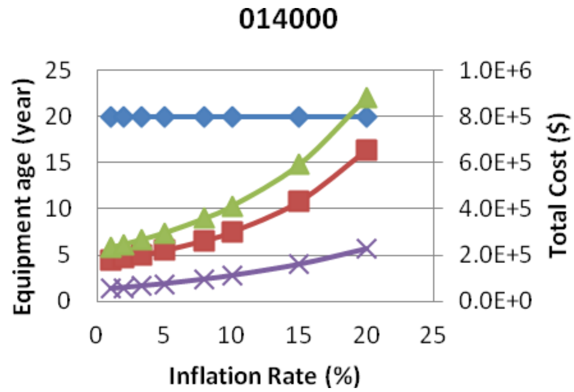
In order to review the level of success achieved from applying the algorithm, the forecasted purchase costs for the classcodes were thoroughly evaluated. The same 75 classcodes identified for the manual testing were again selected for a detailed review of the software algorithm. All 75 classcodes were found to have an increasing forecasted purchase cost for the 20-year horizon. In fact, the algorithm resulted in increasing forecasted purchase costs for all of the classcodes, as intended. It was also discovered from the 75 classcodes selected, that using the inflation adjusted purchase cost had a major impact on the number of classcodes with linear models that passed all three algorithm thresholds. Therefore, it was concluded that removing the effect of inflation from the purchase cost had a significant impact on the data's tendency to possess a measurable trend, both identified and utilized by the software.

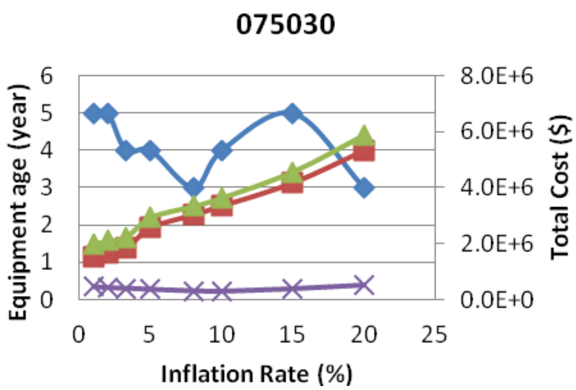
Specifically, the results indicated that the software algorithm generally outputs a forecasted purchase cost based on the halved inflation rate due to the failure of the linear model to meet the goodness of fit threshold. As more TERM data becomes available in future years, this trend may change. The more comprehensive the purchase cost data sets, the more likely a linear model will provide an acceptable fit and be selected; thus, the forecasted purchase cost will be based on the historical data. In either case, the algorithm will continue to provide a robust solution for forecasting the purchase cost with increasing values, as well as encapsulating more intuitive trends.

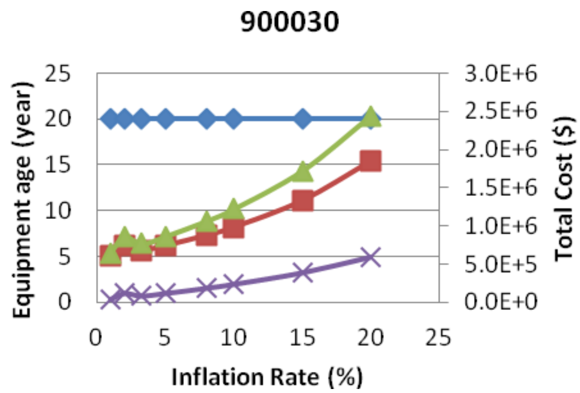
The impacts of future uncertain equipment purchase costs on equipment replacement decision making is also investigated through conducting sensitivity analyses of the inflation rate based on the further testing of the ERO software and result analyses. In the following sections, the impact of the inflation rate on equipment replacement decision making (i.e., the optimal equipment replacement age) and the total cost is depicted in several graphs using a few classcodes for both light and heavy vehicles for both current trend and equal mileage approaches. Such numerical results are presented in detail as follows.

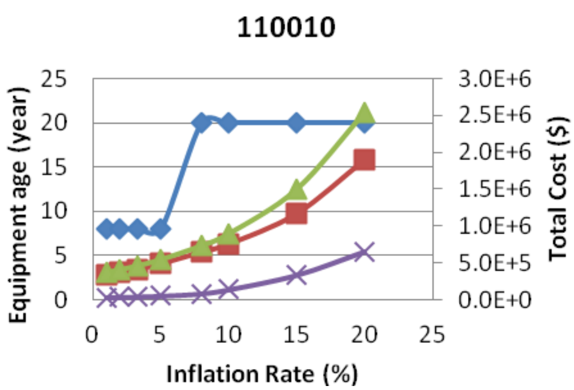
Cost Current Trend Heavyweight

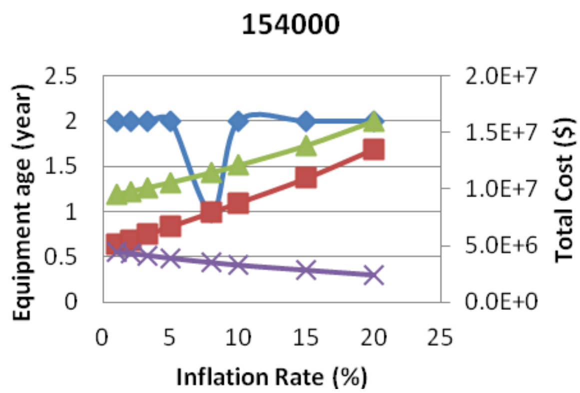


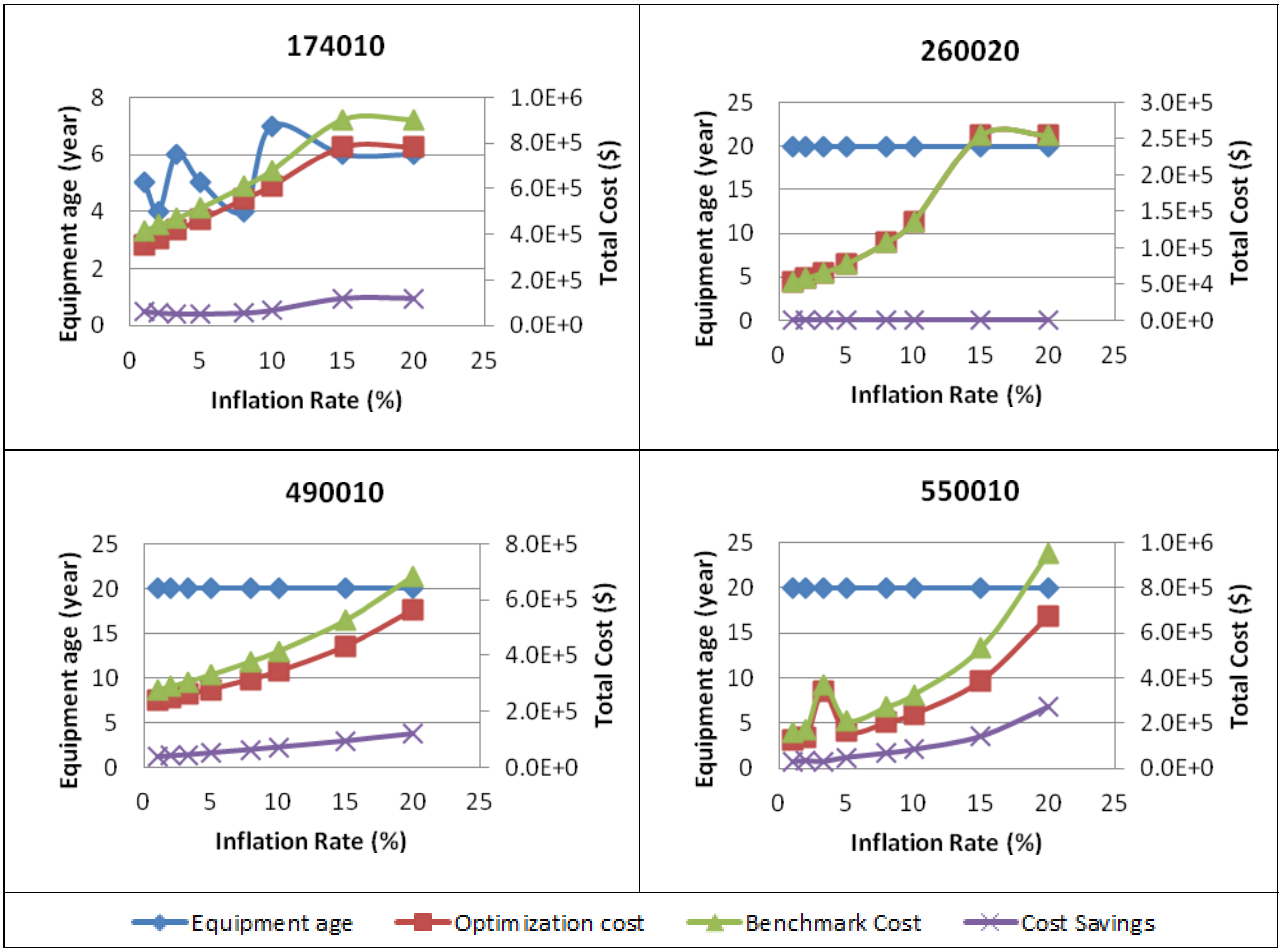




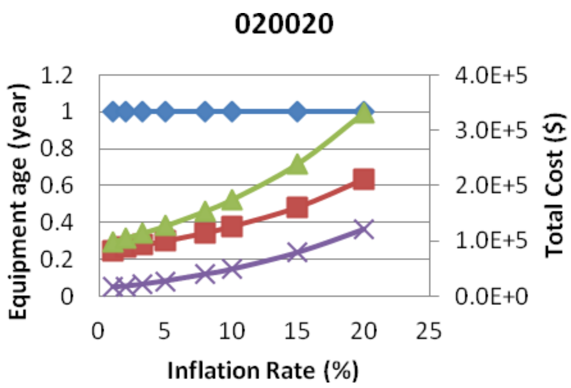


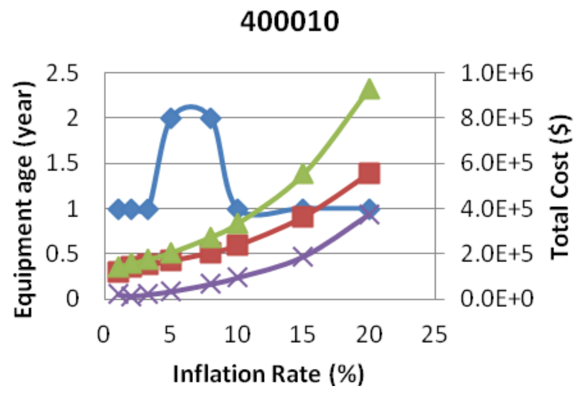


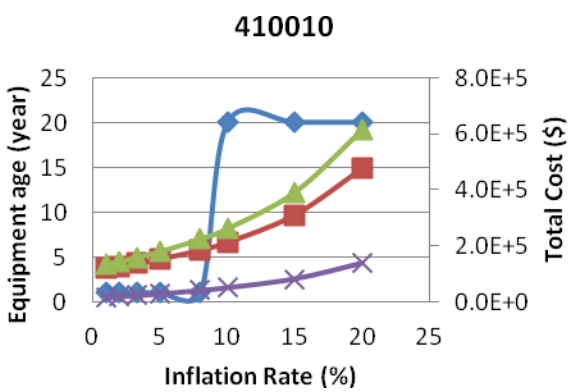


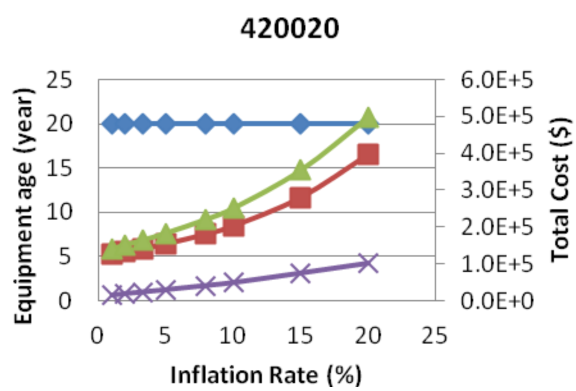

174010
260020
490010
550010
Equipment age (year)
Total Cost ($)
Inflation Rate (%)
0
2
4
6
8
5
10
15
20
25
0.0E+0
2.0E+5
4.0E+5
6.0E+5
8.0E+5
1.0E+6
5.0E+4
1.0E+5
1.5E+5
2.0E+5
2.5E+5
3.0E+5
Equipment age
Optimization cost
Benchmark Cost
Cost Savings

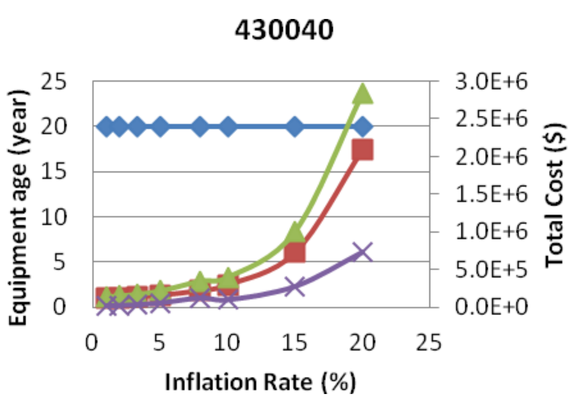
Cost Current Trend Lightweight

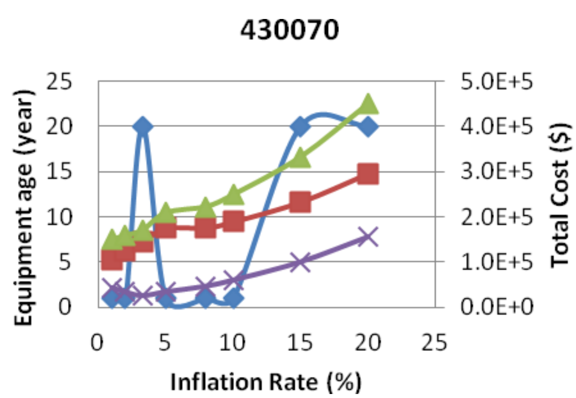


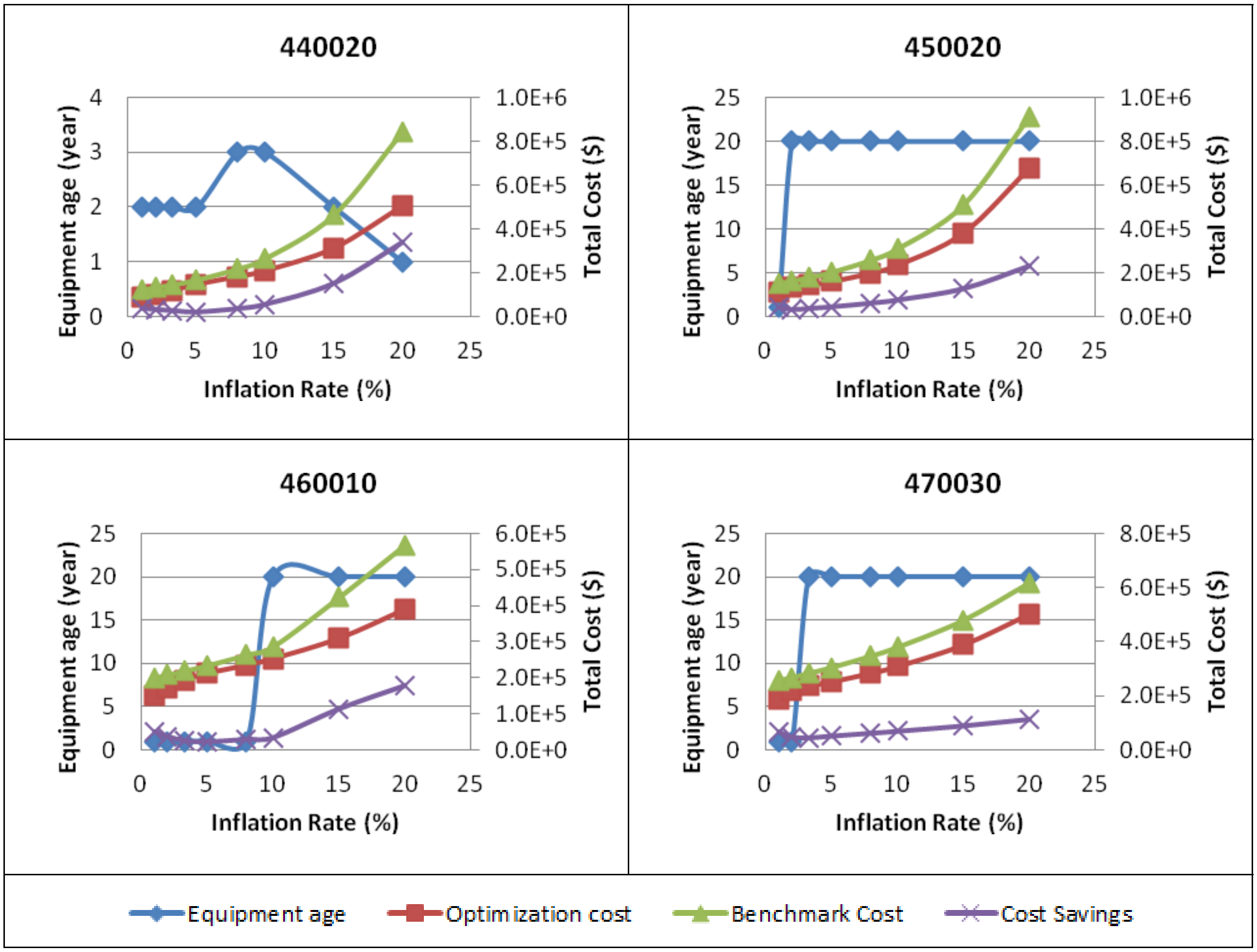




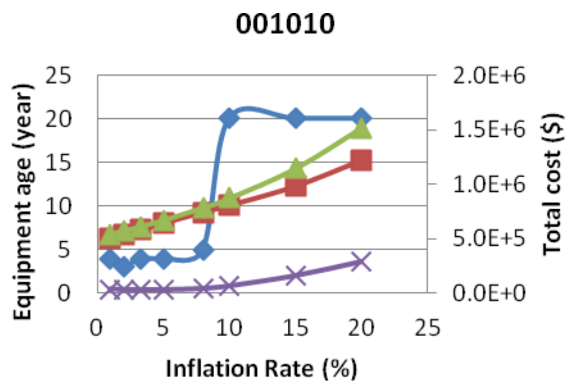


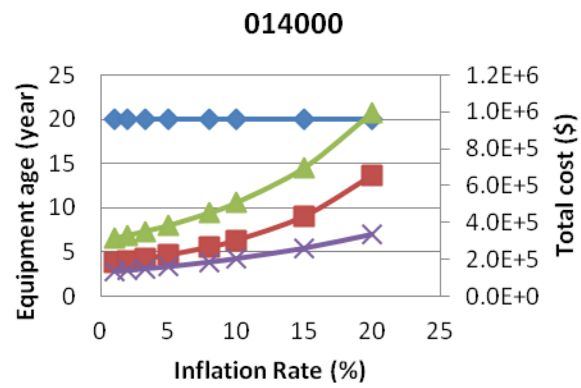


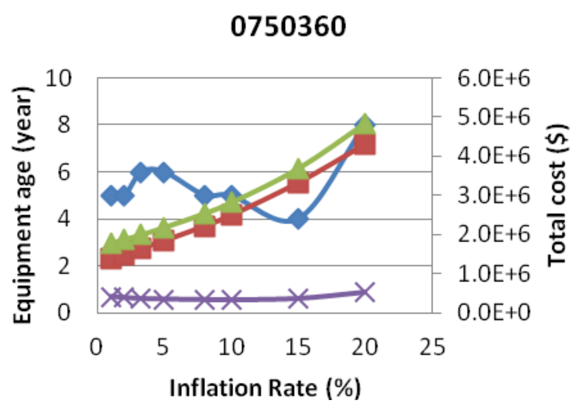


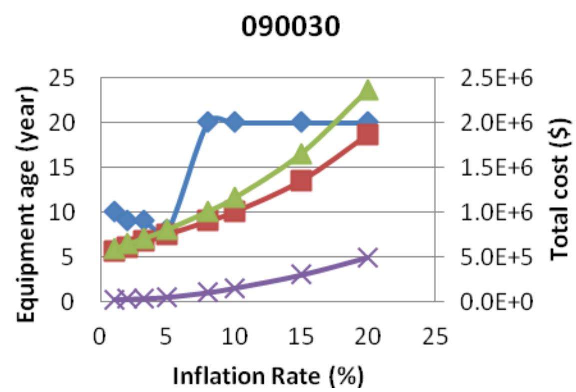

440020
450020
460010
470030
Equipment age (year)
Total Cost ($)
Inflation Rate (%)
Equipment age
Optimization cost
Benchmark Cost
Cost Savings

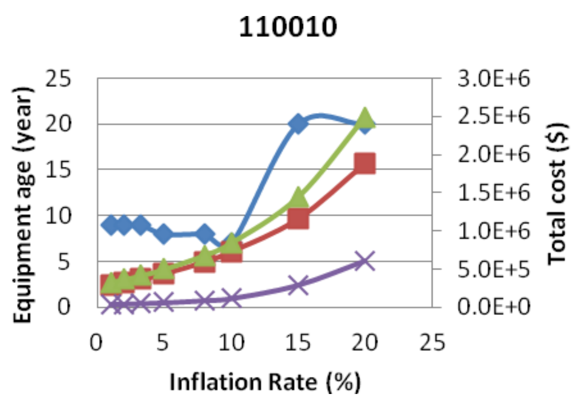
Cost Equal Mileage Heavyweight

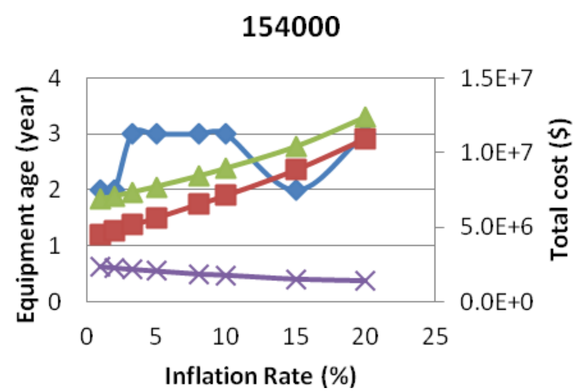


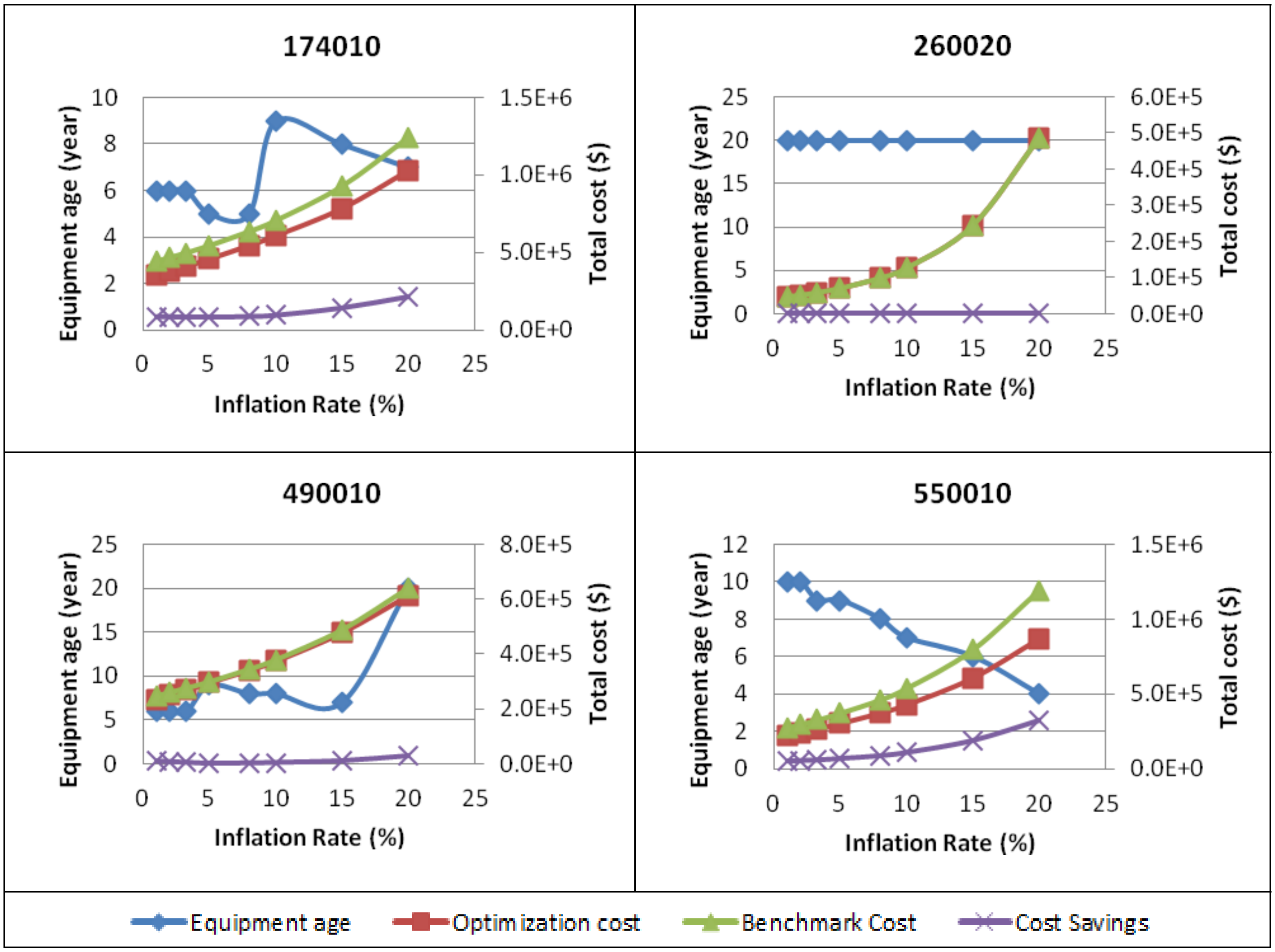




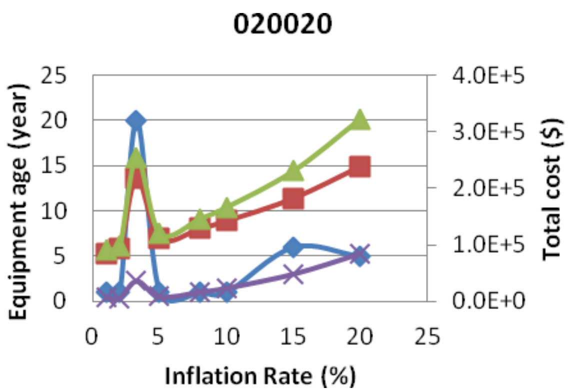


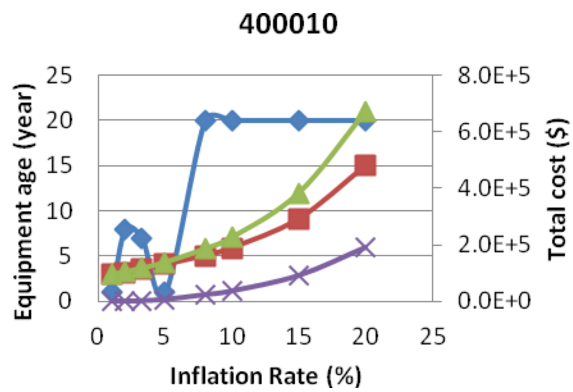


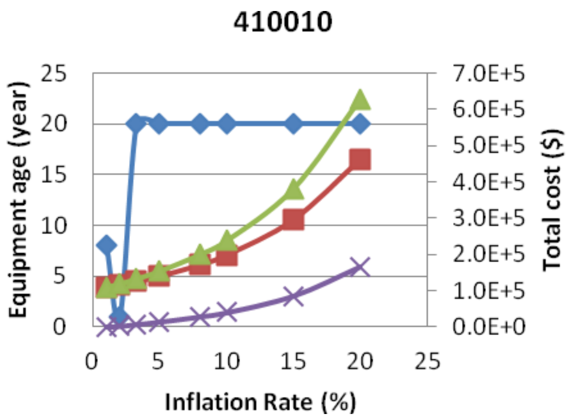


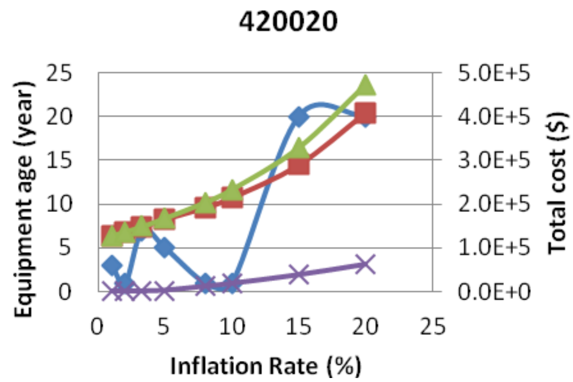

174010
260020
490010
550010
Equipment age (year)
Total cost ($)
Inflation Rate (%)
Equipment age
Optimization cost
Benchmark Cost
Cost Savings

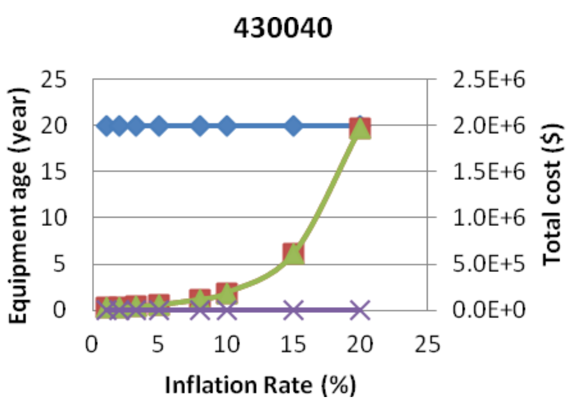
Cost Equal Mileage Lightweight

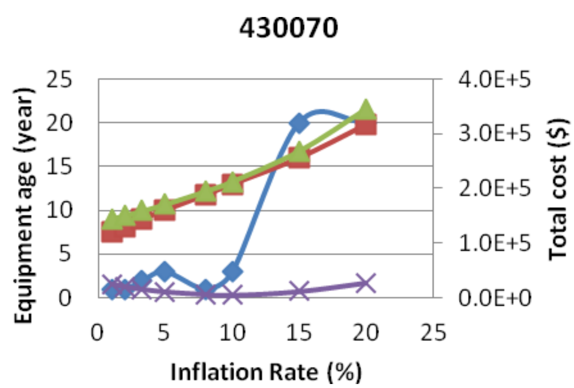












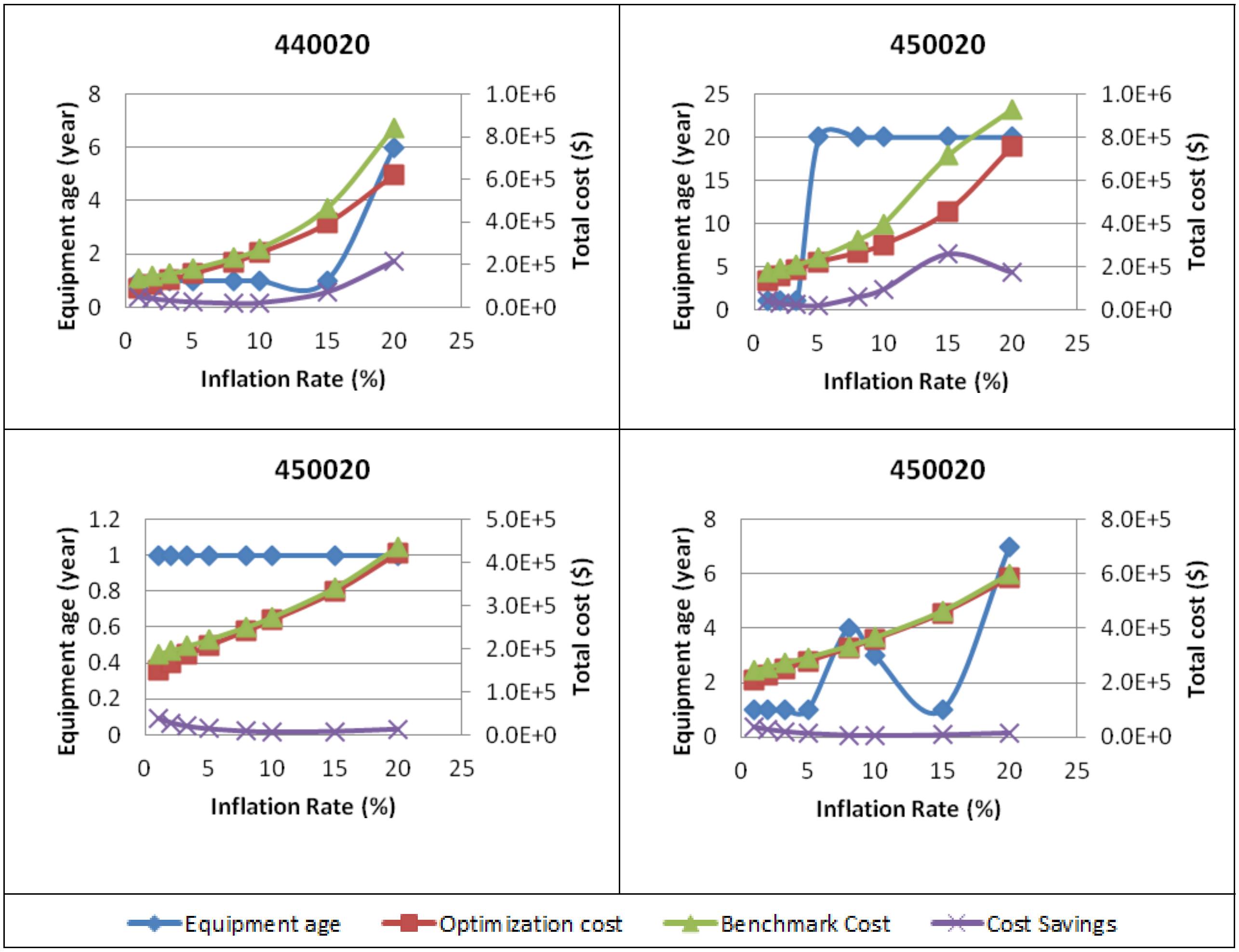


Figure 3.5 Impact of Inflation Rates on Equipment Replacement Decision Making

As can be seen from the graphs in Figure 3.5, several conclusions can be made as follows:

- For Cost Current Trend, inflation rate affects the optimal replacement age generally by increasing the optimal replacement equipment age with higher inflation rates or the equipment age remains constant. Inflation rate causes the benchmark cost to increase faster than the optimization cost. The most rapid increase of the benchmark cost occurs after the inflation rate reaches 10%. Whereas the optimization cost continues to increase gradually with the higher inflation rate.
- For Cost Equal Mileage, inflation rate affects the optimal replacement equipment age of the heavyweight equipment by generally decreasing as the inflation rate increases. There generally is a spike in equipment age at the inflation rate of 10% which afterward the age continues to decrease. Inflation rate affects the optimal replacement equipment age of the lightweight equipment by gradually increase with the increase of the inflation rate. The benchmark cost and optimization cost have similar cost values until the inflation rate reaches 5%. After 5% the benchmark cost increases rapidly.
- The benchmark cost is always higher than the optimization cost and generally the cost savings increases as the inflation rate increases. For Cost Current Trend, the cost savings

increases slowly until the inflation rate of 5% is reached. After the 5% inflation rate the cost savings increases quicker. For Cost Equal Mileage, the cost saving remains constant until the inflation rate of 10% is reached. After the 10% inflation rate the cost savings increases quicker. Cost Current Trend saves more money because it gains more savings at a lower inflation rate than the Cost Equal Mileage.

3.4 Summary

The original strategy for forecasting the purchase cost was based on selecting the best-fit model from a series of linear and nonlinear statistical models created from the available historical data. This approach resulted in some projections yielding a decreasing, and in some cases negative, forecasted purchase cost. To solve this problem, a number of strategies were created and tested in order to establish an algorithm for the software.

These strategies included implementation of a factor of the inflation rate (multiplied by the purchase cost) in place of a statistical model, use of MSRP in place of historical purchase cost, addition of commodity price index variables as predictors, utilization of moving averages for purchase cost, examination of other equations with a high quality of fit (high R-square value), and creation of simple linear models. Ultimately, it was decided that using a simple linear model with a series of threshold tests, designed to ensure a quality forecast, would be applied as the primary option for the software algorithm. It was determined that a linear model would be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of robust application in algorithm form, consistency with future additions to the data sets, and provision of a relatively good fit overall for any trends in the data.

As a contingency, a secondary option utilizing a multiple of the inflation rate, to be applied if the linear model fails the threshold tests, was also implemented as part of the software algorithm. This factor was decided to be one-half of the inflation rates, to be multiplied by the current year’s purchase cost to establish the value for the subsequent year. The algorithm, including a secondary outlier removal process, was then coded into the software so that the updated cost forecasts could be input into the optimization engine and subsequently tested for consistency. The results of these tests indicated that the algorithm was performing appropriately, and the forecasted purchase costs for all classcodes would now be increasing over the 20-year horizon.

The impacts of future uncertain equipment purchase costs on equipment replacement decision making is also investigated through conducting sensitivity analyses of the inflation rate based on the further testing of the ERO software and result analyses. The sensitivity analysis is performed for few classcodes (light and heavy vehicles) for both current trend and equal mileage approaches investigating the impact of inflation rate on the optimal equipment replacement age, total cost and cost savings.

Chapter 4. Cost of Delaying Replacing Equipment

4.1 Introduction

TxDOT's new equipment replacement optimization software (TERM2) produced through project 0-6412 "Equipment Replacement Optimization" (ERO) by our research team can optimize the equipment retain/replace decision process and minimize total costs by making the decision to either keep or replace a unit of equipment at the beginning of each year. Much of the current TERM2 research work and results can be found in Fan et al. (2011a, 2011b, 2012a, 2012b). In addition, the current TERM2 is developed and implemented using a comprehensive DP-based optimization solution methodology. It consists of three main components (Fan et al., 2011a): 1) A SAS macro based data cleaner and analyzer, which undertakes the tasks of raw data reading, cleaning, and analyzing, as well as cost estimation and forecasting; 2) A DP-based optimization engine that minimizes the total cost over a defined horizon; and 3) A Java-based graphical user interface (GUI) that takes parameters selected by users, displays the final results of the optimization, and coordinates the optimization engine and SAS macro data cleaner and analyzer. Figure 2.1, in Chapter 2, shows the flow chart of the solution methodology used in TERM2. The detailed description of each of the three components can be seen from Fan et al. (2011a).

In particular, a DP-based optimization engine, which consists of the DDP- and SDP-based solution approaches, both Bellman's and Wagner's formulations, have been developed and implemented for solving the ERO problem. The ERO 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 forecast, and replacement cost forecast from SAS macro codes.

The following will first present the ERO optimization engine in Section 4.2. Then DP optimization results without budget considerations will be discussed in Section 4.3 in order to lay a foundation for the DP optimization results with budget considerations. DP optimization results with budget considerations are discussed in Section 4.4 and include the presentation of calculating the cost increase when delaying replacement, and discussions about both the second round knapsack programming optimization methodology and numerical results.

4.2 ERO Optimization Engine

As mentioned in Fan et al. (2011a), the proposed DP solution algorithms have been implemented via backward recursion and a DP-based TERM2 solution software has been developed to minimize the total costs.

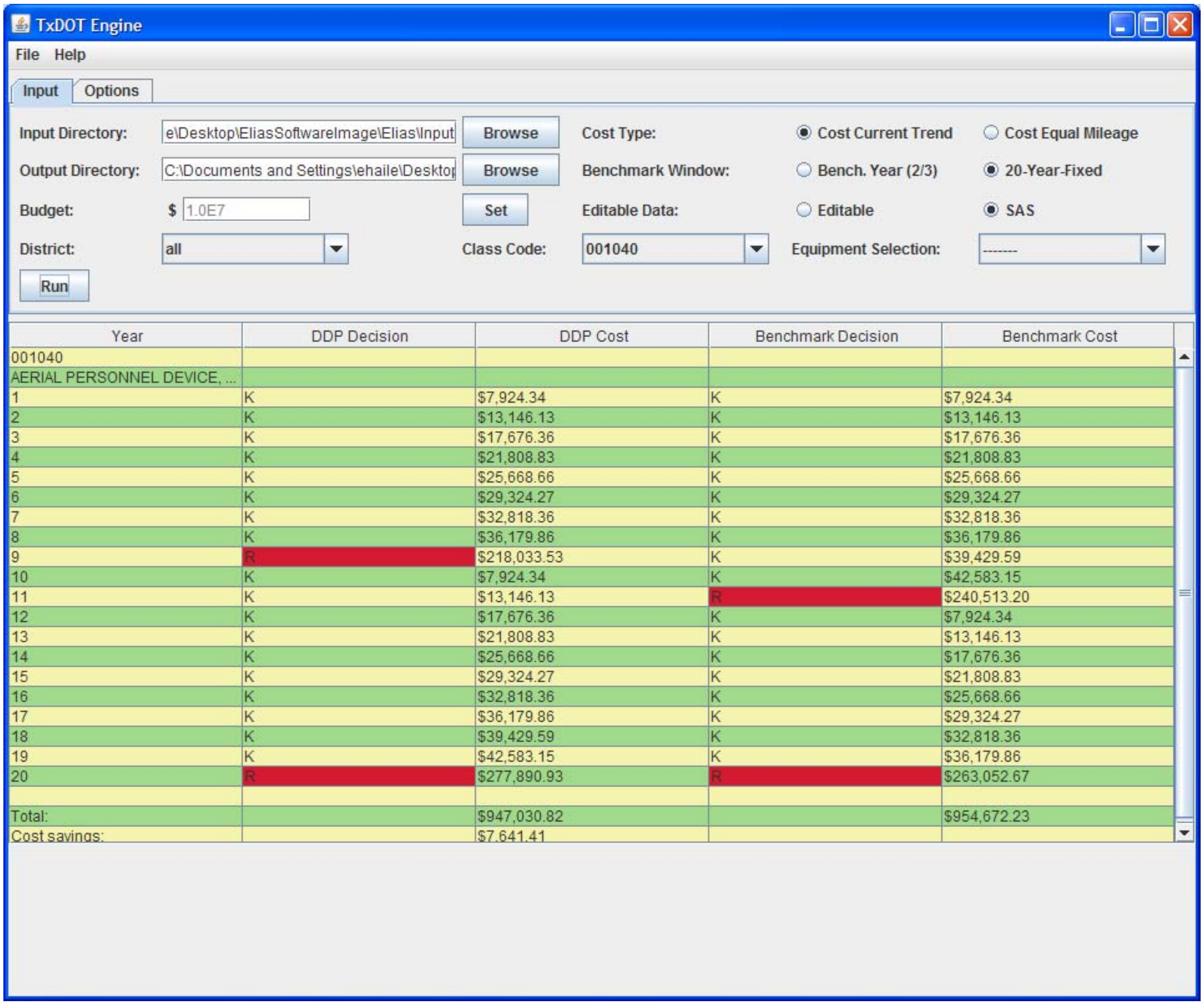
By developing the optimization and evaluation framework to investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced (i.e., determine the increase in cost when delaying replacing equipment), and developing/implementing the second round Knapsack Programming optimization framework, as well as by integrating them with the DP optimization methodology in the new TERM2 software, the ERO under annual budget constraint can now be successfully considered. The developed ERO software in this project is now very general and can be used to make optimal keep/replace decisions for both brand-new and used vehicles, both with and without annual budget considerations, based on the equipment class, age, mileage, salvage value, and replacement cost which come from SAS macro codes. 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 (such results will be discussed in Section 4.3 as background information); 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 (this will be discussed in Section 4.4).

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 considerations, then only the DP optimization will be called upon to determine an 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 of 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 associated 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 (i.e., minimize the total increase in costs incurred to TxDOT) for the user given the specified annual budget for the decision year, and produce a final equipment replacement recommendation file which contains the optimal equipment replacement results in order to embody a mixture of both TxDOT's short-term and long-term interests.

4.3 DP Optimization Results without Budget Consideration

4.3.1 DP GUI Results

Once optimization has been run, the results will be displayed through the GUI, as shown in Figure 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 total cost 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
001040				
AERIAL PERSONNEL DEVICE, ...				
1	K	$7,924.34	K	$7,924.34
2	K	$13,146.13	K	$13,146.13
3	K	$17,676.36	K	$17,676.36
4	K	$21,808.83	K	$21,808.83
5	K	$25,668.66	K	$25,668.66
6	K	$29,324.27	K	$29,324.27
7	K	$32,818.36	K	$32,818.36
8	K	$36,179.86	K	$36,179.86
9	R	$218,033.53	K	$39,429.59
10	K	$7,924.34	K	$42,583.15
11	K	$13,146.13	R	$240,513.20
12	K	$17,676.36	K	$7,924.34
13	K	$21,808.83	K	$13,146.13
14	K	$25,668.66	K	$17,676.36
15	K	$29,324.27	K	$21,808.83
16	K	$32,818.36	K	$25,668.66
17	K	$36,179.86	K	$29,324.27
18	K	$39,429.59	K	$32,818.36
19	K	$42,583.15	K	$36,179.86
20	R	$277,890.93	R	$263,052.67
Total:		$947,030.82		$954,672.23
Cost savings:		$7,641.41		

Figure 4.1 DDP Results in GUI

4.3.2 Exporting DP Results

The GUI table shown in Figure 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 saving it to any location desired (as shown in Figure 4.2). 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, the user can double click the CSV file created in order to display the results in Excel. In the event that Excel does not open automatically, Excel can be opened first and the CSV file subsequently loaded from the software.

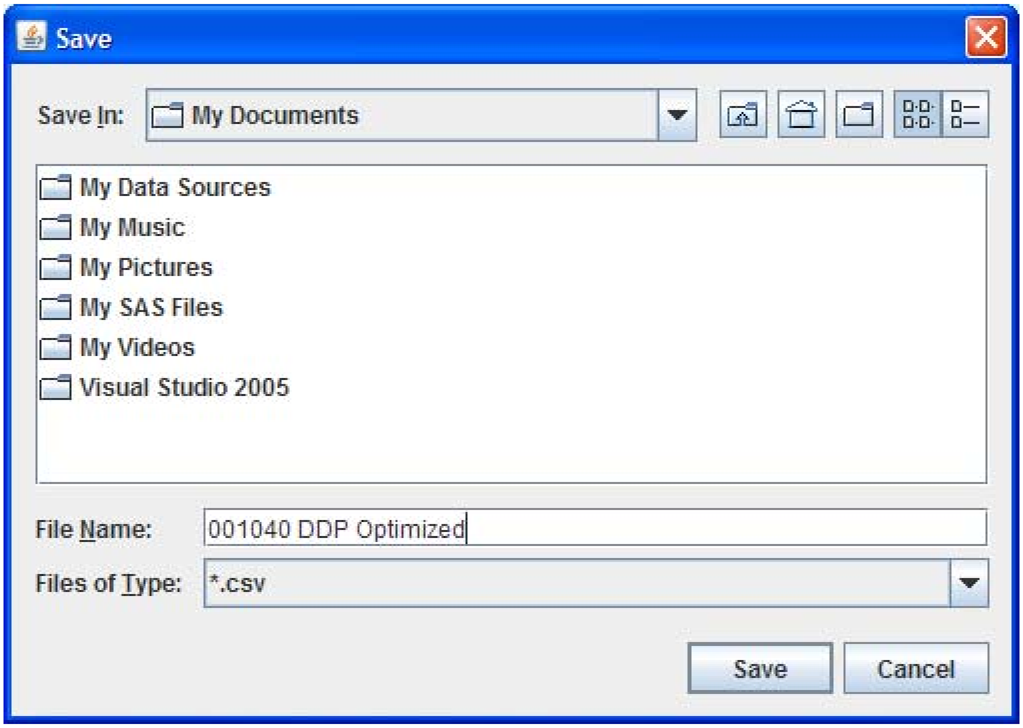
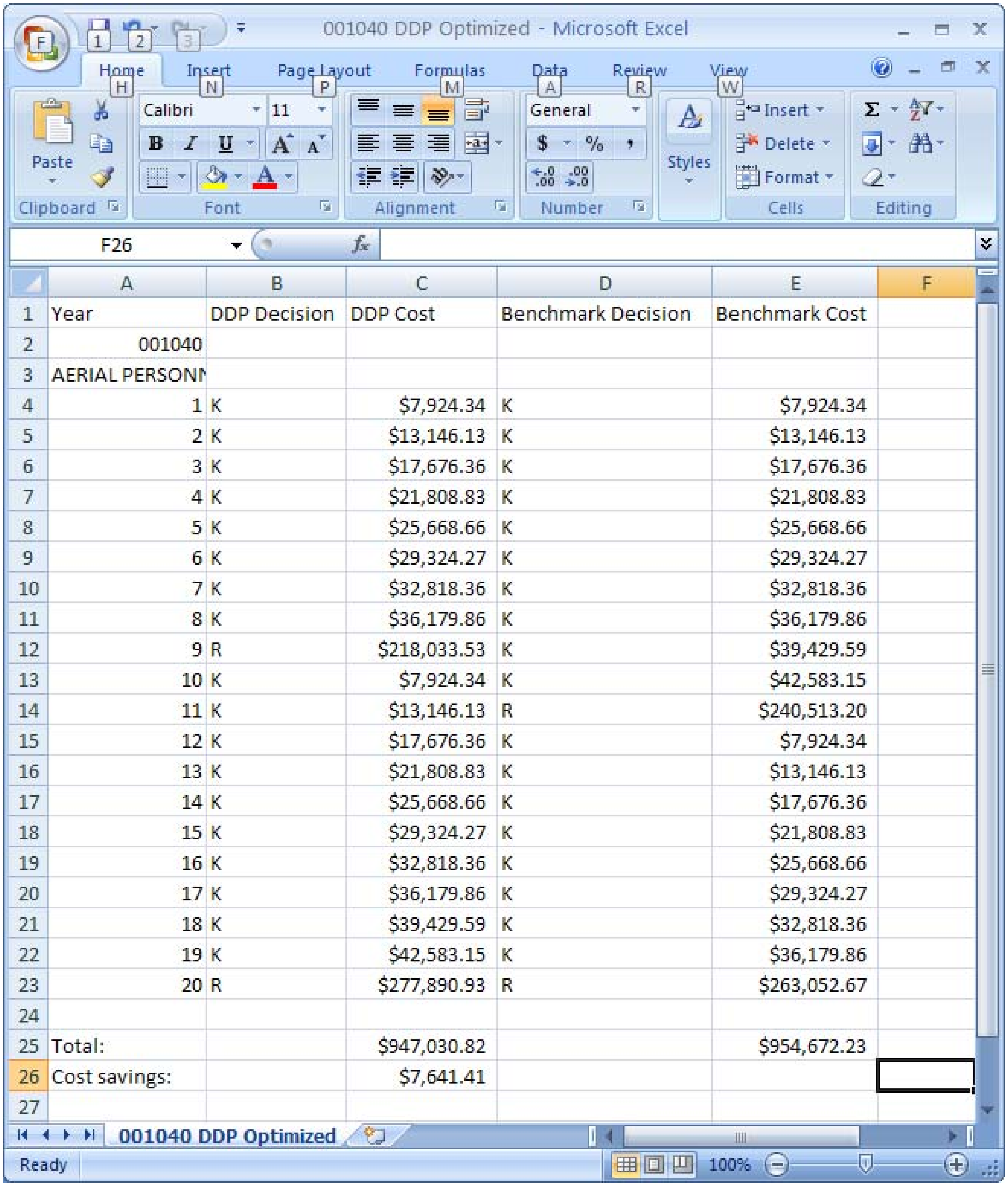


Figure 4.2 Save as CSV

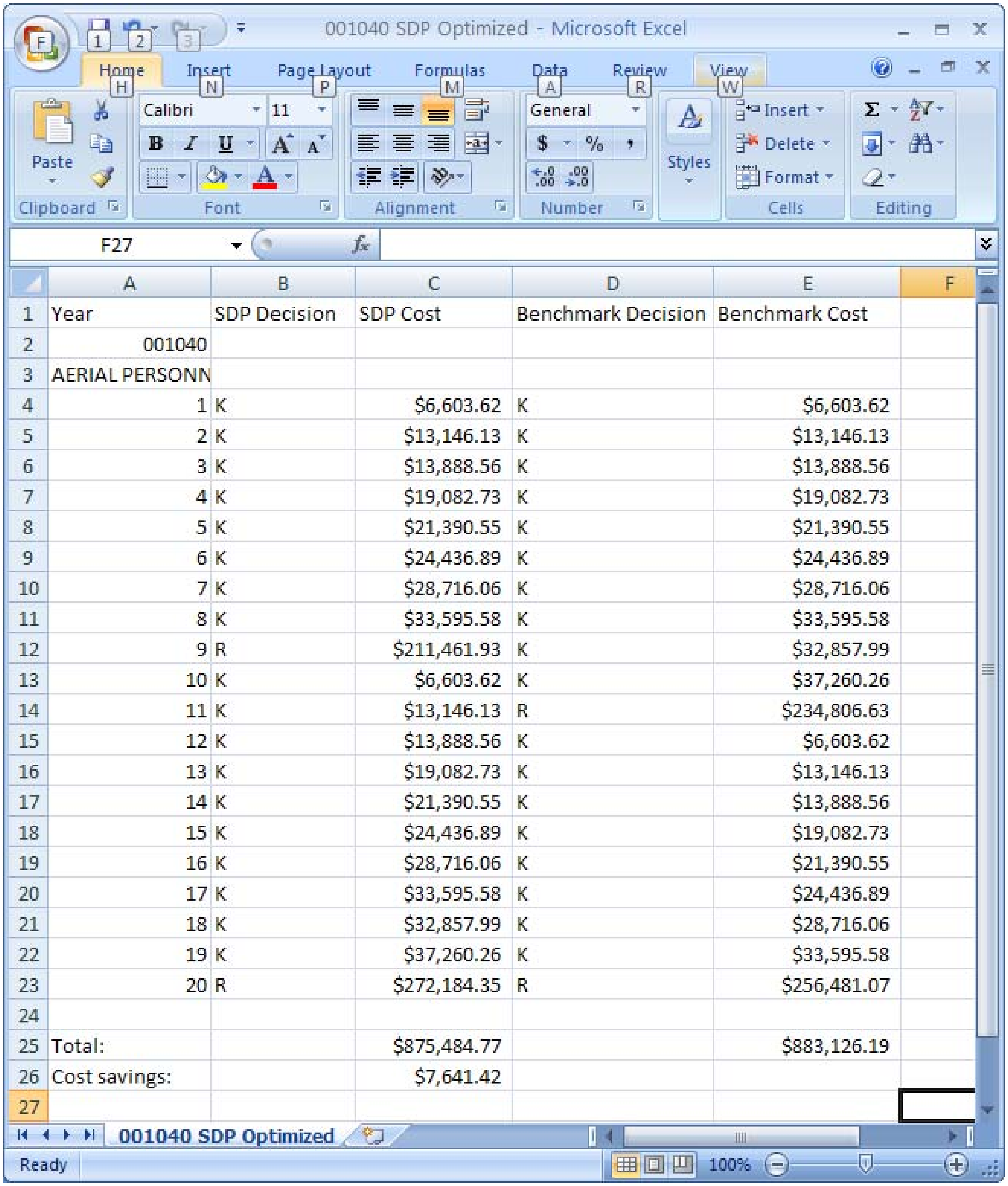
When opened in Excel, the results will look similar to Figures 4.3 (for DDP results) and 4.4 (for SDP results). Note that the first column is the number of years into the future, starting from the beginning of the current fiscal year (i.e., the decision year). The second column refers to the optimized (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, shown in Figure 4.3, the DDP approach saves a total estimated cost of $7,641.41 over the 20-year window when compared against the current benchmark rules used by TxDOT.



	A	B	C	D	E	F
1	Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost	
2	001040					
3	AERIAL PERSONN					
4	1	K	$7,924.34	K	$7,924.34	
5	2	K	$13,146.13	K	$13,146.13	
6	3	K	$17,676.36	K	$17,676.36	
7	4	K	$21,808.83	K	$21,808.83	
8	5	K	$25,668.66	K	$25,668.66	
9	6	K	$29,324.27	K	$29,324.27	
10	7	K	$32,818.36	K	$32,818.36	
11	8	K	$36,179.86	K	$36,179.86	
12	9	R	$218,033.53	K	$39,429.59	
13	10	K	$7,924.34	K	$42,583.15	
14	11	K	$13,146.13	R	$240,513.20	
15	12	K	$17,676.36	K	$7,924.34	
16	13	K	$21,808.83	K	$13,146.13	
17	14	K	$25,668.66	K	$17,676.36	
18	15	K	$29,324.27	K	$21,808.83	
19	16	K	$32,818.36	K	$25,668.66	
20	17	K	$36,179.86	K	$29,324.27	
21	18	K	$39,429.59	K	$32,818.36	
22	19	K	$42,583.15	K	$36,179.86	
23	20	R	$277,890.93	R	$263,052.67	
24						
25	Total:		$947,030.82		$954,672.23	
26	Cost savings:		$7,641.41			
27						

Figure 4.3 DDP Results in Excel

Similarly, Figure 4.4 follows the same format as Figure 4.3. However, it represents the results for the SDP 2-Level approach (please refer to Fan et al. 2011a for detail). 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, shown in Figure 4.4, the SDP approach saves a total estimated cost of $7,641.41 over the 20-year window when compared against the current benchmark rules used by TxDOT.



	A	B	C	D	E	F
1	Year	SDP Decision	SDP Cost	Benchmark Decision	Benchmark Cost	
2	001040					
3	AERIAL PERSONN					
4	1	K	$6,603.62	K	$6,603.62	
5	2	K	$13,146.13	K	$13,146.13	
6	3	K	$13,888.56	K	$13,888.56	
7	4	K	$19,082.73	K	$19,082.73	
8	5	K	$21,390.55	K	$21,390.55	
9	6	K	$24,436.89	K	$24,436.89	
10	7	K	$28,716.06	K	$28,716.06	
11	8	K	$33,595.58	K	$33,595.58	
12	9	R	$211,461.93	K	$32,857.99	
13	10	K	$6,603.62	K	$37,260.26	
14	11	K	$13,146.13	R	$234,806.63	
15	12	K	$13,888.56	K	$6,603.62	
16	13	K	$19,082.73	K	$13,146.13	
17	14	K	$21,390.55	K	$13,888.56	
18	15	K	$24,436.89	K	$19,082.73	
19	16	K	$28,716.06	K	$21,390.55	
20	17	K	$33,595.58	K	$24,436.89	
21	18	K	$32,857.99	K	$28,716.06	
22	19	K	$37,260.26	K	$33,595.58	
23	20	R	$272,184.35	R	$256,481.07	
24						
25	Total:		$875,484.77		$883,126.19	
26	Cost savings:		$7,641.42			
27						

Figure 4.4 SDP Results in Excel

In these two examples, the cost to replace the equipment unit belonging to this classcode (001040) on the 9th year is the same 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 9 years or replace on year 20, and the benchmark decision was to replace at years 11 and 20. Therefore, when the equipment unit is replaced on year 20, the optimal decision requires the salvage of a 9-year-old piece of equipment instead of the 11-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 9th year.

4.4 DP Optimization Results with Budget Consideration

4.4.1 Calculating Cost Increase when Delaying Replacement

The research team has developed the following optimization and evaluation framework to investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced (i.e., determine the increase in cost when delaying replacing equipment). First, we get the optimal solution path and its total cost value through DDP/SDP without accounting for the replacement delay and the uncertain annual budget constraint; Second, we change this path to a path that delays replacing the equipment by a certain number of years (e.g., it can be a number determined by the software user through the GUI but must fall into the range which is defined as the TxDOT current benchmark replacement year plus or minus 3 and less than 20 years) and calculate the minimum total cost for the delayed path using DDP/SDP from that point on; Third, we quantify the increase in cost, which is equal to the difference in the total cost value between the optimized path and the delayed path. In so doing, the cost to the department of NOT replacing equipment, when it should be replaced but the optimal timely replacement suggested by the software is impossible due to uncertain future funding levels, can be calculated.

We have successfully implemented such optimization and evaluation framework for the replacement delay logic in the current TERM2 software using the best computer data structures, which will explicitly take into account both computation speed and memory usage. Also, the ERO under annual budget constraint is considered by incorporating the logic of delaying replacing equipment and the Knapsack Programming into the dynamic programming (including both Deterministic DP and Stochastic DP) approaches. The optimal equipment replacement decision now can be made using two rounds of optimization (DDP/SDP + Knapsack Programming, another linear integer programming model) to maximize the benefits (i.e., minimize the total increase in costs or maximize the total cost savings incurred to TxDOT due to optimal equipment replacement under the annual budget constraint) to embody a mixture of both TxDOT's short-term and long-term interests. Certainly, all solutions have been comprehensively tested and validated throughout this project.

As the software runs, user delay files are automatically created and stored in the Output Directory (currently located in folder \TERM Data\Output). These files are "user_delays.csv; user_delay_increase.csv"; and "Delay.csv", as well as "Replacement_Final_Recomendation.csv" (as results of the second-round knapsack optimization whenever the ERO for any or many pieces of equipment are considered for replacement under a budget constraint as specified by the fleet manager). 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.

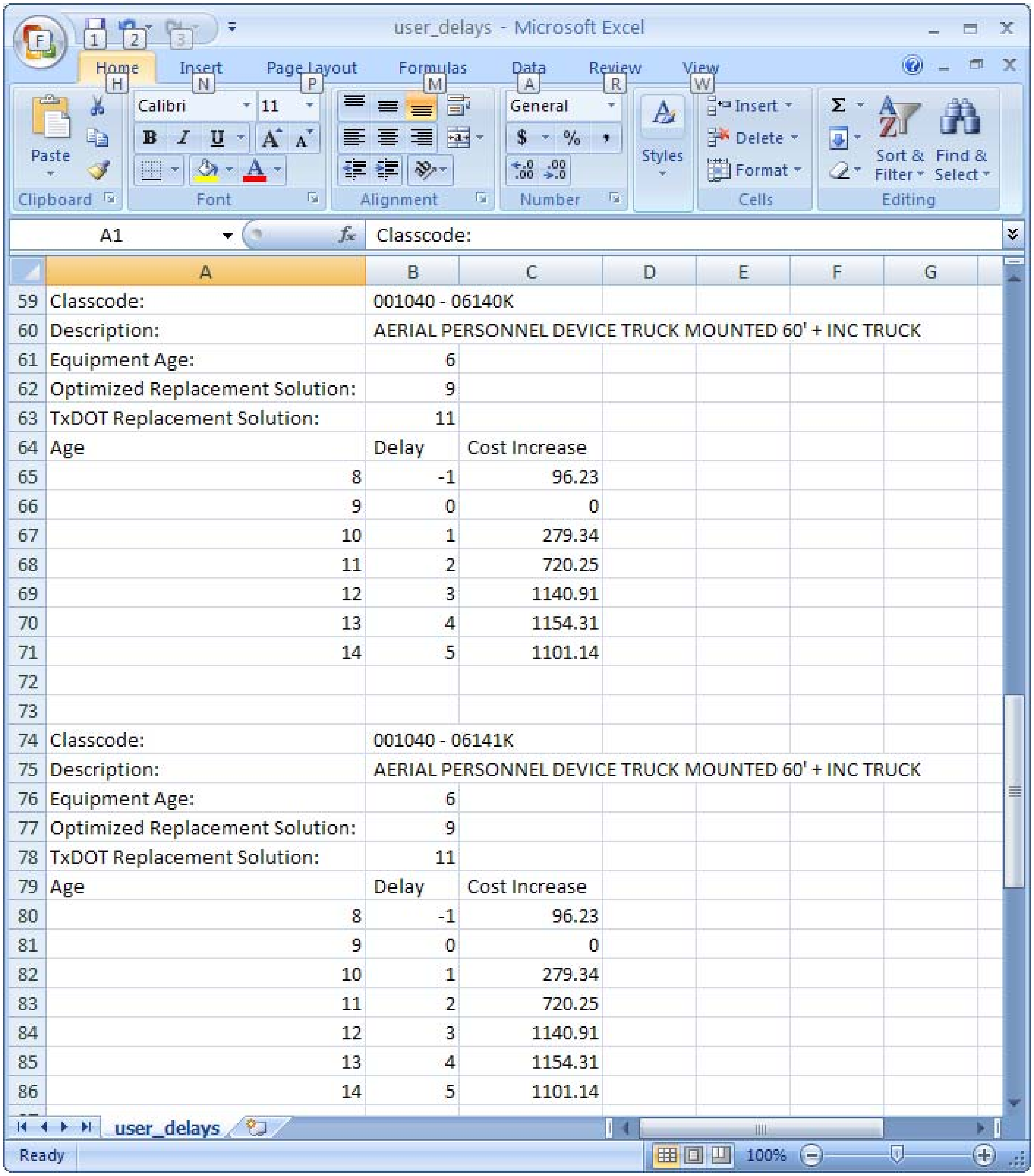
Note that, even though the term “Delay” is found in the titles of these output files, they are generated every time the DP optimization is run whether or not any Delay time is specified by the user. Also, the first and second files, “user_delays.csv” and “user_delay_increase.csv”, respectively, are outputs 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 for any or many pieces of equipment but NOT at the classcode level.

The subsequent 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, all District, ClassCode “001040”, all Equipment Selection, no Delay, and the SDP 2-Level approach and the Bellman approach selected.

4.4.2 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 4.5, if Equipment Unit “001040 – 06140K” is replaced 1 years earlier than the optimized replacement (i.e., Delay = -1) then that decision will cause a total cost increase of $96.23 and its age at the time of replacement will be 8 as compared to the optimized replacement age of 9. Also, if replacement of Classcode “001040” Equipment Unit “06141K” is delayed by two years (i.e., Delay = 2) then that decision will cause a total cost increase of $720.25 and its age at the time of replacement will be 11, as compared to the optimized replacement age of 9.

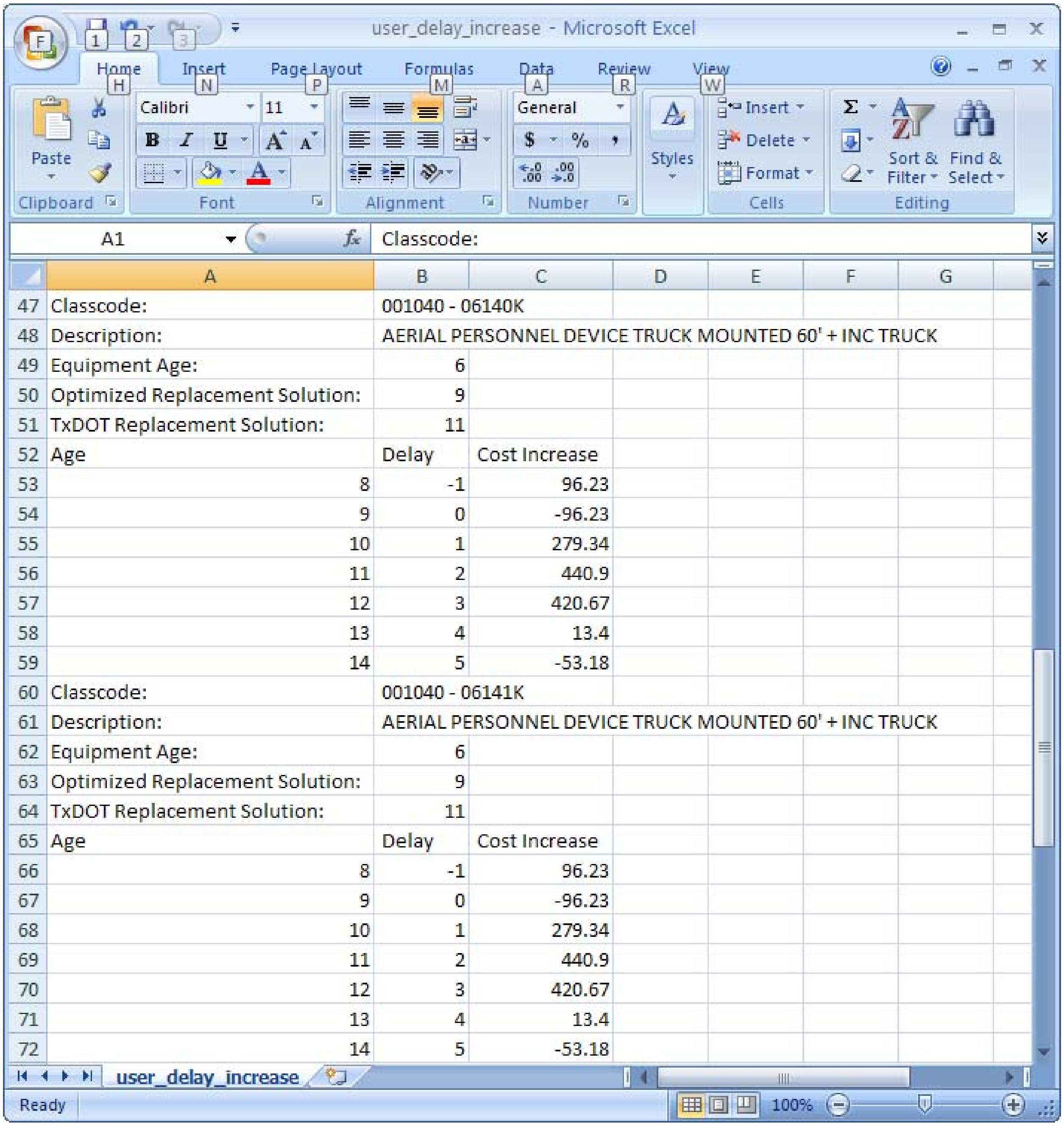


	A	B	C
59	Classcode:	001040 - 06140K	
60	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 60' + INC TRUCK	
61	Equipment Age:	6	
62	Optimized Replacement Solution:	9	
63	TxDOT Replacement Solution:	11	
64	Age	Delay	Cost Increase
65	8	-1	96.23
66	9	0	0
67	10	1	279.34
68	11	2	720.25
69	12	3	1140.91
70	13	4	1154.31
71	14	5	1101.14
72			
73			
74	Classcode:	001040 - 06141K	
75	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 60' + INC TRUCK	
76	Equipment Age:	6	
77	Optimized Replacement Solution:	9	
78	TxDOT Replacement Solution:	11	
79	Age	Delay	Cost Increase
80	8	-1	96.23
81	9	0	0
82	10	1	279.34
83	11	2	720.25
84	12	3	1140.91
85	13	4	1154.31
86	14	5	1101.14

Figure 4.5 User_Delays.csv

4.4.3 User_Delays_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 each additional year. For example, in Figure 4.6, if Equipment Unit "001040 – 06140K"is replaced 2 year later than the optimized decision (i.e., Delay = 2), then that decision will cause an additional cost increase of $440.9 compared to the decision of replacement 1 year later than the optimized decision (i.e., Delay = 1). As mentioned in Figure 4.5, the total cost increase of replacing 2 year late is equal to $720.25. This value is equal to the cost increase of Delay = 2 plus Delay = 1, as found in Figure 4.6, or $279.34 + $440.9 = $720.25.



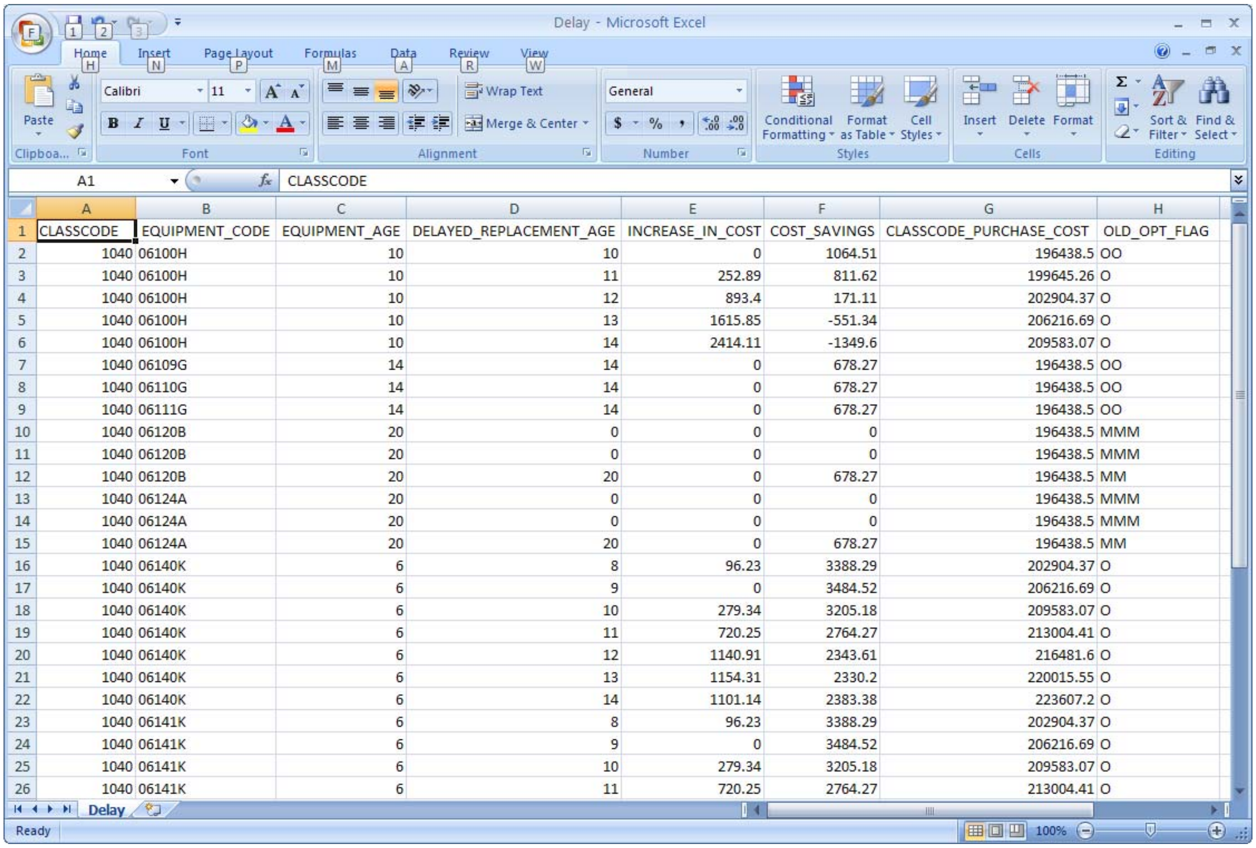
	A	B	C
47	Classcode:	001040 - 06140K	
48	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 60' + INC TRUCK	
49	Equipment Age:	6	
50	Optimized Replacement Solution:	9	
51	TxDOT Replacement Solution:	11	
52	Age	Delay	Cost Increase
53	8	-1	96.23
54	9	0	-96.23
55	10	1	279.34
56	11	2	440.9
57	12	3	420.67
58	13	4	13.4
59	14	5	-53.18
60	Classcode:	001040 - 06141K	
61	Description:	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 60' + INC TRUCK	
62	Equipment Age:	6	
63	Optimized Replacement Solution:	9	
64	TxDOT Replacement Solution:	11	
65	Age	Delay	Cost Increase
66	8	-1	96.23
67	9	0	-96.23
68	10	1	279.34
69	11	2	440.9
70	12	3	420.67
71	13	4	13.4
72	14	5	-53.18

Figure 4.6 User_Delay_Increase.csv

4.4.4 Delay.csv

As mentioned earlier, this file is used as the direct input into the second round of knapsack programming optimization and each column (as shown in Figure 4.7) 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 at the current year.
- M or O – Denotes a candidate for replacement 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	1040	06100H	10	10	0	1064.51	196438.5	OO
3	1040	06100H	10	11	252.89	811.62	199645.26	O
4	1040	06100H	10	12	893.4	171.11	202904.37	O
5	1040	06100H	10	13	1615.85	-551.34	206216.69	O
6	1040	06100H	10	14	2414.11	-1349.6	209583.07	O
7	1040	06109G	14	14	0	678.27	196438.5	OO
8	1040	06110G	14	14	0	678.27	196438.5	OO
9	1040	06111G	14	14	0	678.27	196438.5	OO
10	1040	06120B	20	0	0	0	196438.5	MMM
11	1040	06120B	20	0	0	0	196438.5	MMM
12	1040	06120B	20	20	0	678.27	196438.5	MM
13	1040	06124A	20	0	0	0	196438.5	MMM
14	1040	06124A	20	0	0	0	196438.5	MMM
15	1040	06124A	20	20	0	678.27	196438.5	MM
16	1040	06140K	6	8	96.23	3388.29	202904.37	O
17	1040	06140K	6	9	0	3484.52	206216.69	O
18	1040	06140K	6	10	279.34	3205.18	209583.07	O
19	1040	06140K	6	11	720.25	2764.27	213004.41	O
20	1040	06140K	6	12	1140.91	2343.61	216481.6	O
21	1040	06140K	6	13	1154.31	2330.2	220015.55	O
22	1040	06140K	6	14	1101.14	2383.38	223607.2	O
23	1040	06141K	6	8	96.23	3388.29	202904.37	O
24	1040	06141K	6	9	0	3484.52	206216.69	O
25	1040	06141K	6	10	279.34	3205.18	209583.07	O
26	1040	06141K	6	11	720.25	2764.27	213004.41	O

Figure 4.7 Delay.csv

4.5 Knapsack Programming

The knapsack problem is a task in combinatorial optimization: Given a set of n items, 1 through n. Each item has a value of v_i and a weight w_i. The maximum weight that can be carried in the knapsack is W. The goal is to 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; Nemhauser and Wolsey, 1999). Mathematically, the unbounded 0-1 knapsack programming model (which restricts the number x_i of copies of each kind of item to zero or one) can be formulated as follows:

$$\text{Maximize} \quad \sum_{i=1}^{n} v_i x_i$$

$$\text{subject to} \quad \sum_{i=1}^{n} w_i x_i \leq W$$

$$x_i \in \{0,1\}$$

On the other hand, the bounded 0-1 knapsack programming problem considers an additional constraint (which restricts the number x_i of copies of each kind of item to a maximum integer value c_i). In this case, the bounded 0-1 knapsack programming problem can be mathematically formulated as:

Maximize $\sum_{i=1}^{n} \quad w_i x_i \leq W$

subject to $\sum_{i=1}^{n} \quad w_i x_i \leq W$

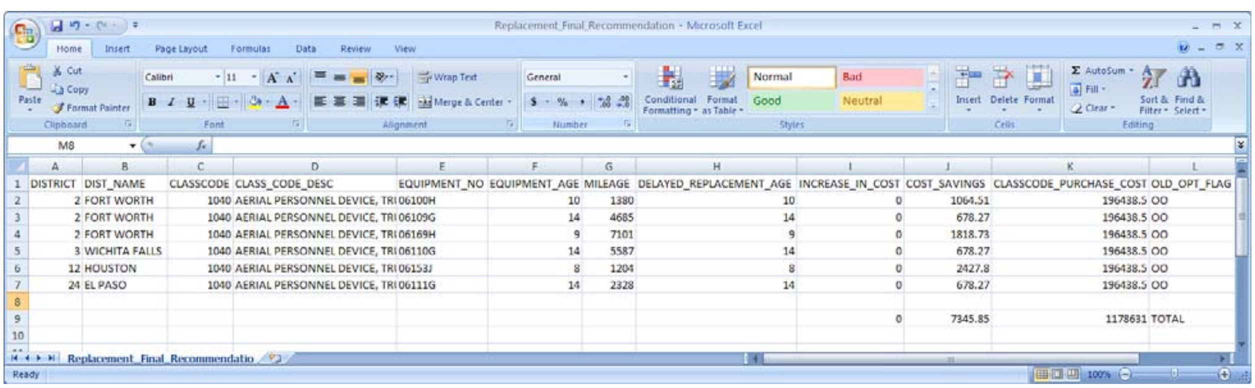
$x_i \in \{0, 1, \ldots, c_i\}$

Note that 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 that belong to each classcode. 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 case of an unbounded 0-1 knapsack programming ERO model application, there is no maximum number specified by the fleet manager for the equipment units to be selected for replacement that belong to any given classcode. However, in the bounded 0-1 knapsack programming ERO model application, the fleet manager may specify a maximum number of candidate equipment units for replacement that belong to some given classcodes in order to balance the replacement budget across the classcodes. It should be noted that either problem can be handled with minor changes.

4.6 Replacement_Final_Recomendation.csv

This file is arranged similarly to the file "Delay.csv" described in Section 4.4.4. 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 total estimates of the Increase in Cost compared to the optimized decision, the Cost Savings versus the benchmark decision, and the Classcode Purchase Costs are provided at the bottom of each column, respectively in Figure 4.8.



DISTRICT	DIST_NAME	CLASSCODE	CLASS_CODE_DESC	EQUIPMENT_NO	EQUIPMENT_AGE	MILEAGE	DELAYED_REPLACEMENT_AGE	INCREASE_IN_COST	COST_SAVINGS	CLASSCODE_PURCHASE_COST	OLD_OPT_FLAG
2	FORT WORTH	1040	AERIAL PERSONNEL DEVICE, TRI	06100H	10	1380	10	0	1064.51	196438.5	OO
2	FORT WORTH	1040	AERIAL PERSONNEL DEVICE, TRI	06109G	14	4685	14	0	678.27	196438.5	OO
2	FORT WORTH	1040	AERIAL PERSONNEL DEVICE, TRI	06169H	9	7101	9	0	1818.73	196438.5	OO
3	WICHITA FALLS	1040	AERIAL PERSONNEL DEVICE, TRI	06110G	14	5587	14	0	678.27	196438.5	OO
12	HOUSTON	1040	AERIAL PERSONNEL DEVICE, TRI	06153J	8	1204	8	0	2427.8	196438.5	OO
24	EL PASO	1040	AERIAL PERSONNEL DEVICE, TRI	06111G	14	2328	14	0	678.27	196438.5	OO
								0	7345.85	1178631	TOTAL

Figure 4.8 Replacement_Final_Recomendation.csv

4.7 Summary

The DP optimization results with budget consideration are discussed in detail in Section 4.4, which includes the presentation of calculating cost increases when delaying replacement, and the discussions about both the second round knapsack programming optimization methodology and its numerical results. The developed knapsack programming model 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.

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. Next, based on these cost inputs, the Knapsack programming at the second round of optimization (which can explicitly consider any annual budget constraints and possibly some other constraints specified by the fleet manager) is developed and used to select the equipment units for annual replacement from a solution space that consists of all of the equipment units that are eligible for replacement. The main objective of this Knapsack programming is to maximize the benefits produced (i.e., minimize the total cost increases due to delay for equipment replacement) in order to embody a mixture of both TxDOT's short-term and long-term interests. Preliminary results indicate that a significant amount of cost savings can be estimated by using the developed solution methodology when using an annual budget of $15 million for TxDOT's current TERM data.

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.

Chapter 5. Improving Downtime, O&M Costs, and Mileage Forecasting

5.1 Introduction

The original strategy for estimating down time was to use one universal rate for all of the classcodes in the TxDOT TERM database. However, this estimate was limited, as different vehicle types are likely to incur a different cost due to being out of service. Therefore, a unique rate was established for each individual classcode based on techniques found from a review of relevant literature. Since down time is part of the overall O&M costs for each equipment unit, its proper estimation was a critical component in establishing forecasts for O&M costs.

It was found that the strategy for forecasting the O&M costs developed for project 0-6412 required some modifications, in a similar manner to that of the purchase costs. The original approach involved the development of multiple statistical models to forecast the equipment purchase cost. Upon implementation of the above strategy, some forecasted O&M costs were found to be much higher or lower than expected, and in some extreme cases, negative. This prompted the research team to undergo a full review of the forecasts for each classcode. It was discovered that several issues involving forecasted O&M costs were prevalent due to a variety of reasons. This finding led to the development of a strategy intended to create more robust forecasts of O&M costs for all classcodes and associated circumstances. The estimation of down time along and obstacles discovered using the original O&M cost forecasting approach, as well as the development of an alternate strategy and its subsequent implementation into the software package, are further described in the following sections.

5.2 Estimating the Cost of Downtime

In an effort to improve the ability of the optimization engine to develop a replacement plan for equipment, all life-cycle costs were considered. This led to the investigation of the cost of down time. It was determined that a simple, universal estimate for down time rate might not be sufficient to cover the extensive range of equipment types and subsequent failure scenarios. Therefore, a number of references were reviewed for additional information about estimating down time costs for equipment fleets. It was discovered that estimating the cost of down time can have a profound impact on decisions relative to fleet management. Furthermore, a number of strategies were uncovered from reports conducted for the United States (US) Army, as well as local governments.

In a study conducted for the US Army by Virginia Tech University, costs related to down time were investigated, as well as strategies for their estimation (Fuerst et al. 1991). It was determined that down time costs could be divided into two categories: tangible costs, and consequential costs. Tangible costs were described as those associated directly with the breakdown of a piece of equipment or vehicle, including labor, materials, and repair resources. These costs were described as relatively simple to track, depending on well-defined circumstances to quantify. On the other hand, consequential costs were identified as those associated with a failure that impact an entire project, department, or organization. These costs are much more difficult to quantify accurately and require more information to effectively monitor. It was offered that a rough estimate of consequential costs could be obtained for a vehicle by multiplying the percent of down time by the number of planned hours of use and the hourly cost of replacement or rental. It was concluded that effective fleet management requires a balance between capital costs versus those costs associated with operating at an inferior level.

It was determined that to more accurately estimate the costs associated with vehicle or equipment failure, the hourly cost of resources affected by the failure, the time necessary to react, and the frequency of failure need to be taken into account where failure causes system-wide impacts (Fuerst et al. 1991). A series of formulas were developed as part of the study for estimating the cost components, including information relative to impact lag, impact duration, and cumulative costs. The procurement of substantial information for each failure would be required for the most accurate estimation of down time costs. However, implementing the strategy at a low level of complexity could be accomplished for monitoring a particularly large fleet. Ultimately, the most crucial information required for estimating down time costs for each vehicle or piece of equipment was identified to be the number of breakdowns, the number of hours broken down each month, and the number of hours in working condition each month.

Another report was completed by the Rand Corporation for the US Army (Pint et al. 2008). The study was completed for the purpose of implementing a fleet management strategy for rubber-wheeled vehicles commissioned by the Army at bases throughout the world. At the heart of the report was the development of statistical models used to assess vehicle age and other predictor variables relative to repair costs and down time. These models were then implemented in an optimal vehicle replacement model. The study investigated approximately 21,700 vehicles, including fifteen types at twelve locations. Of primary interest for prediction of repair costs and down time were variables for vehicle age, annual usage, odometer reading, location, and type of vehicle. Overall, it was determined that repair costs and down time increase with vehicle age, a trend that tapered off with older vehicles. A similar but weaker relationship was found using vehicle usage as a predictor.

It was noted in the report that the models required an estimate for the cost of down time and that labor data associated with mission critical failures was available (Pint et al. 2008). Down time, as estimated with respect to vehicle age and usage, was investigated by determining the number of days a vehicle was inoperative for each repair and computing the average annual down time. Repair costs were implemented as an annual average amount for parts and labor. In all, down time was determined to increase with age, as represented by the probability of down time exceeding zero, and was also discovered to be influenced by location. The cost of down time was defined as the cost of being without a piece of equipment and was estimated using the cost of renting a replacement vehicle. Furthermore, this cost was augmented by a risk factor. The daily rental cost was multiplied by a risk factor of three if the identified failure prevented completion of a mission. If the failure was not deemed to be mission-critical, typically based on the availability of another fleet vehicle, then only the daily rental rate was utilized as the estimate. It was determined that the use of a risk factor in the estimation of down time costs had a large impact on the results obtained by the optimal replacement model.

Further review of fleet management and the related cost of down time led to the examination of several reports for local governments. The first was a fleet management audit for the City of Palo Alto, California (2010). It was found that the city recently saved millions of dollars by freezing the replacement of non-urgent fleet vehicles. The city further improved efficiency by developing a strategy for adequately funding fleet repair and maintenance. It was also determined that the city needed to better manage their repair parts inventory. As an overall strategy for fleet management, the report outlined a number of recommendations. The report recommended revising policies to develop cost-effective utilization criteria and to clarify replacement criteria and guidelines for take-home use of vehicles. Additional recommendations included rotating vehicles between departments to better balance their utilization, freezing the replacement of under-utilized vehicles, making sure vehicles identified for replacement were actually removed from the fleet, and renting vehicles when possible. These recommendations where shown to require complete data about city vehicles, including an up-to-date database of pooled vehicles identifying their availability.

Another audit report was examined involving a multi-year review of fleet management for Clark County, Washington (2004). Again, it was recommended to eliminate underutilized vehicles (less than 6,000 mi per year) and to investigate why "replaced" vehicles were often retained. It was determined that these issues contributed to a fleet that was losing value without the benefit of extensive use. In particular, the pooled vehicles were significantly underutilized and it was recommended to either decrease the size of the pool and rent vehicles as required or develop a strategy to increase utilization, including development of a cost-per-mile performance measure for vehicles and implementation of a minimum mileage standard.

A fleet management study for the City of Chattanooga, Tennessee (2002) was also reviewed. As identified by others, the need for a detailed database of information about the fleet was recommended for future reference. Additional recommendations included monitoring the quality of maintenance and repair practices, making preventative maintenance a priority, and determining the life-cycle costs relative to new equipment purchases, including availability of repair parts and familiarity of maintenance staff with equipment.

The acclaimed success of the fleet management department for the City of Winnipeg, Manitoba, Canada was also investigated (St. George, 2007). It was determined that the city's vehicle fleet was oversized and that many older vehicles were frequently in repair, requiring additional vehicles to cover the excessive down time. The city decided to upgrade to a newer, more reliable fleet and emphasize preventative maintenance. Through the process, the city adopted life-cycle cost management practices to help track purchases, repairs, and maintenance.

The investigation of fleet management and the cost of down time from the various reports resulted in the identification of a few underlying themes. The reports underscored the importance of developing a detailed and up-to-date database for both fleet vehicles and available repair parts. The reports demonstrated the importance of preventative maintenance and the quality of services and repairs. Issues were also frequently identified with respect to the underutilization of vehicles and accurately accounting for life-cycle costs. Furthermore, it was identified that the accurate estimation of down time costs is imperative for developing a strategy for optimal vehicle replacement.

The reports conducted for the US Army identified a number of strategies for estimating down time cost. These strategies could involve specific information about fleet operations, possible failures, and the costs or impacts associated with those failures, or they could involve a minimal amount of information including the number and length of down time related events. However, both reports also identified the use of equipment or vehicle rental rates as an estimate for down time. This would result in an estimate that is proportional to the type of equipment in repair. While this doesn't involve estimating labor expenses and other consequential costs, a risk factor could be implemented as a simplified approach to account for those costs which are difficult to quantify.

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

The rental rate was chosen as an adequate assessment of down time cost based on the established precedence for its use and due to the limited information available relative to down time in the TxDOT database. The information provided identifies only the number of annual, down time hours incurred for each vehicle. To accomplish the task of assigning a down time cost, the rental rate for each classcode was determined using information obtained from various sources in the equipment and vehicle rental industry. An appropriate match and subsequent rental rate was found for many of the classcodes. However, several rates had to be estimated based on similar vehicle types or for equipment assigned tasks of similar significance. In the end, a daily rental rate was established for 197 classcodes found in the database. An hourly rental rate was also estimated from the daily rate for consistency with the information provided in the database regarding down time (hours).

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

The rental rates and risk factors were reviewed and approved by the TxDOT fleet manager prior to implementation into the optimization software. It should be noted that the finalized down time rates are provided in Excel format in the input folder as part of the program's file structure. This file can be reviewed and the rental rates, risk factors, and subsequent down time rates manually adjusted by the fleet manager, as deemed appropriate in the analysis process. See Figure 5.1 for an image of the editable Excel file.

	A	B	C	D	E
1	Code	Daily Rate	Base Hourly Rate	Risk Factor	Adjusted Hourly Rate
2	1010	650	82	1	82
3	1020	650	82	1	82
4	1030	865	109	1	109
5	1040	1500	188	1	188
6	1050	650	82	1	82
7	2000	350	44	1	44
8	10010	550	69	2	138
9	10020	450	57	2	114
10	11010	835	105	3	315
11	12010	200	25	2	50
12	12020	350	44	2	88
13	12030	835	105	2	210
14	12040	835	105	2	210
15	13010	835	105	2	210
16	13020	450	57	2	114
17	14000	250	32	2	64
18	16000	400	50	2	100
19	17000	550	69	2	138
20	18000	700	88	2	176
21	19000	1000	125	3	375
22	19010	1500	188	3	564
23	20020	75	10	1	10
24	20030	75	10	1	10
25	25010	75	10	1	10

Figure 5.1 Editable Excel Table with Risk Factors and Down Time Rates

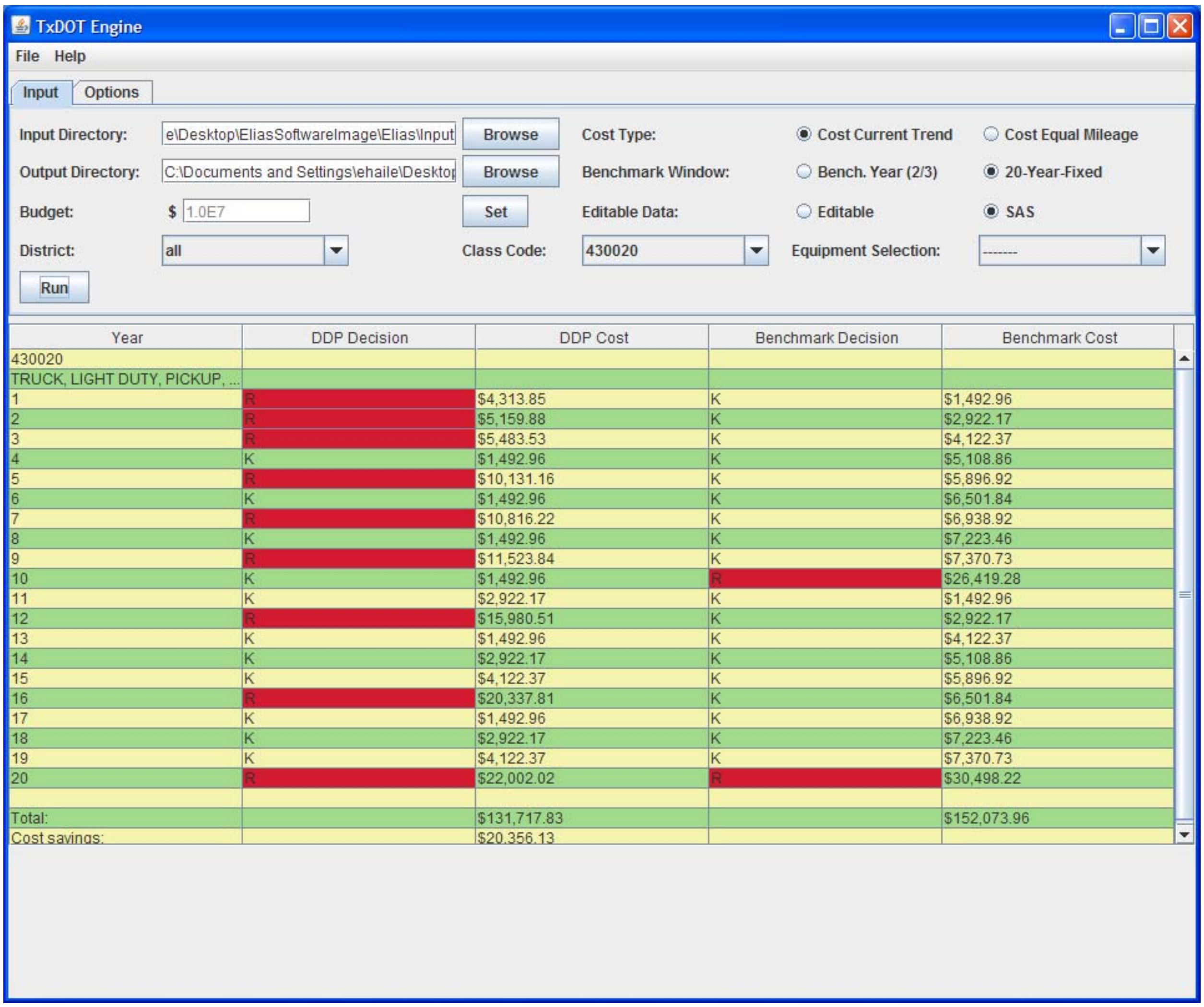
The above figure shows a portion of the Excel file containing the derived values, including: code (equipment classcode), daily (rental) rate, base hourly (rental) rate, risk factor, and adjusted down time rate. Due to the fact that some vehicles and equipment units have large amounts of down time recorded in the database, these rates can have a substantial impact on estimates of O&M costs. The detailed assessment of these O&M costs was undertaken as part of evaluating preliminary optimization results.

5.3 Estimating Annual O&M Costs and Mileage

In addition to establishing a practical rate for down time hours for each individual classcode, the overall O&M costs were evaluated. To derive the O&M costs for each vehicle or equipment unit, nine data fields provided in the TxDOT TERM database are summed. These fields include all costs coded as repair expenses, gas, diesel, oil, other fuel, hydraulic and other fluids, down time, parts, and labor. Several issues were identified from a thorough review of the resulting numbers and subsequent optimization results. It was determined that a software algorithm be developed for SAS to evaluate the O&M costs for each classcode and establish the best possible methodology for forecasting these costs for the ERO horizon. The following sections identify a number of issues discovered from the in-depth review of the ERO results and O&M cost data, the solutions identified for improving the cost forecasts, and the algorithm developed for implementing the solution strategies into the software.

5.3.1 Review of Current Methods

Since the optimization's keep versus replace decision is based on a comparison of the purchase cost less the salvage value versus the O&M costs, a thorough evaluation of the O&M costs, as with the purchase cost forecasts, was required. It was determined from preliminary optimization results that many light duty vehicles were being recommended for replacement within the first three years of purchase. This is clearly a counterintuitive result. Below, Figure 5.2 illustrates an output from the ERO software with this type of result for classcode 430020 (light-duty pickup truck).



Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost
430020				
TRUCK, LIGHT DUTY, PICKUP, ...				
1	R	$4,313.85	K	$1,492.96
2	R	$5,159.88	K	$2,922.17
3	R	$5,483.53	K	$4,122.37
4	K	$1,492.96	K	$5,108.86
5	R	$10,131.16	K	$5,896.92
6	K	$1,492.96	K	$6,501.84
7	R	$10,816.22	K	$6,938.92
8	K	$1,492.96	K	$7,223.46
9	R	$11,523.84	K	$7,370.73
10	K	$1,492.96	R	$26,419.28
11	K	$2,922.17	K	$1,492.96
12	R	$15,980.51	K	$2,922.17
13	K	$1,492.96	K	$4,122.37
14	K	$2,922.17	K	$5,108.86
15	K	$4,122.37	K	$5,896.92
16	R	$20,337.81	K	$6,501.84
17	K	$1,492.96	K	$6,938.92
18	K	$2,922.17	K	$7,223.46
19	K	$4,122.37	K	$7,370.73
20	R	$22,002.02	R	$30,498.22
Total:		$131,717.83		$152,073.96
Cost savings:		$20,356.13		

Figure 5.2 Software Output Display with Early Replacement Recommendations for Classcode 430020

Upon investigation of the issue, it was found that many of these vehicles had high, early O&M costs as forecasted by the models. An in-depth review of the recorded O&M costs for these classcodes, as well as many others, revealed that these costs were noticeably high, particularly in the first two years of deployment. This included a number of the individual O&M cost fields, including repair expenses and down time. With new down time rates established, including those higher than initially coded, in order to better represent the cost of losing certain mission critical pieces of equipment, this problem was even more perceptible.

It was concluded that some adjustments to the data would be required by the software to properly generate applicable forecasting models for O&M costs. A discussion with TxDOT fleet management staff (progress meeting on February 1, 2012) revealed that the early repair costs and associated down time, particularly for the first two years of operation, were likely associated with make-ready costs for vehicles and equipment and were thus, coded inadequately for the ERO process. It was decided that these costs are not the true O&M costs intended to be captured and evaluated as part of the decision algorithm. Therefore, a logical adjustment would need to be made to the raw data to properly forecast true O&M costs.

5.3.2 Adjustments of Annual O&M Costs and Mileage Forecasts

As part of the overall O&M cost totals, it was determined that the coded values for repair expenses, as well as down time, labor, and parts costs would need to be adjusted. Those expenses associated exclusively with operations, including gas, diesel, oil, other fuel, and hydraulic and other fluids would remain as originally coded. In addition, any adjustment would be made for the first two years alone, as any repair expenses beyond that point could be more realistically considered to be true maintenance.

The adjustments included moving all repair expenses entered for the first two years of operation from that field to the net adjusted capital field. That way, make-ready costs, including upgrades to vehicles, could be captured more appropriately. Furthermore, down time, labor, and parts costs were adjusted to one-tenth of their original value. It was determined that some costs coded in these fields may adequately account for oil changes and general maintenance and should remain non-zero; however, these costs would be minimal compared to some of the values observed in the data. Down time entries were found to exceed 100 hours in some cases as reported in the first year of operation and were believed to be associated with vehicles waiting for make-ready modifications. These adjustments resulted in significantly lower O&M costs in the first two years for all equipment classcodes.

To test the impact of the adjustments, seven light duty and seven heavy duty vehicles were selected for comprehensive evaluation. A comparison was made of the unadjusted O&M costs versus the adjusted O&M costs to determine how the modifications might impact the trends in annual O&M cost forecasting and, ultimately, the ERO decision process. The average annual, unadjusted O&M costs for the seven light duty classcodes chosen are shown in Figure 5.3, below.

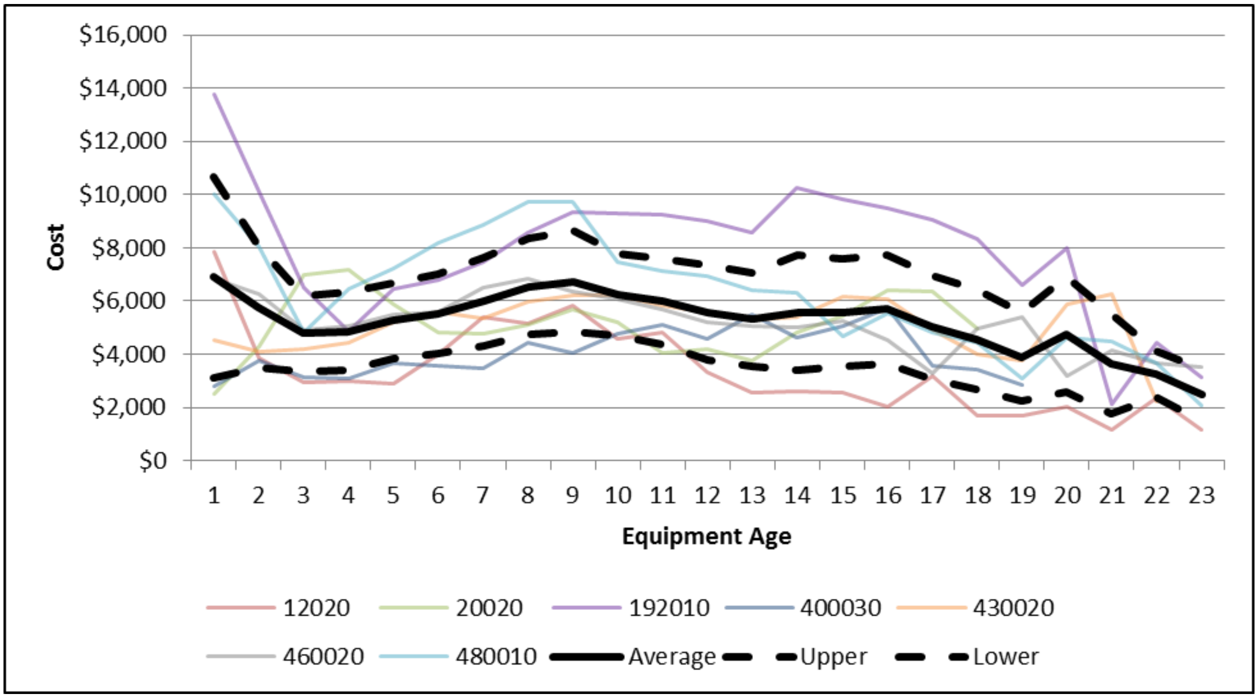


Figure 5.3 Original Average O&M Costs for Select Light Duty Vehicles

The above figure illustrates the trends for the selected light duty vehicles in terms of average O&M costs using the numbers as originally coded and analyzed (i.e., no adjustments to the first two years of operation and a $25 per hour down time rate). The figure highlights the issue with high early O&M costs. It also sheds light on another issue with the data. It illustrates how the O&M costs reach a peak at about the 10-year old mark and then taper off toward the latter years of the equipment's life cycle. The fact that O&M costs are decreasing with age after a point is not intuitive and is not consistent with trends identified in the literature, particularly with the US Army fleet (Pint et al. 2008). This trend suggests that as vehicles have gotten older, there has been a tendency for them to be used less by TxDOT personnel and they have been, therefore, incurring lower O&M costs. This trend is expected to change as future data becomes available due to TxDOT's recent right-sizing efforts. It is likely that the impact of this process has not permeated through the data. Nonetheless, this trend was identified as a possible complication for forecasting O&M costs and the implications and remedial strategy will be discussed in more detail in Section 5.3.3.

For the above classcodes the graph indicates lower utilization of these vehicle types after about 10 years of age. The upper and lower bounds, identified in the legend, correspond to the 95th percentile limits of the data. Figure 5.4 shows the trend for the same light duty vehicles in terms of average O&M costs using the adjusted values for the first two years. This includes the removal of repair expenses and 90-percent of the original down time, parts, and labor costs, as well as a down time cost adjusted to coincide with the rental rate for each individual classcode. The figure illustrates the change in O&M costs in the early years, but understandably, does not correct for the existing phenomenon with the lower cost/utilization as equipment ages.

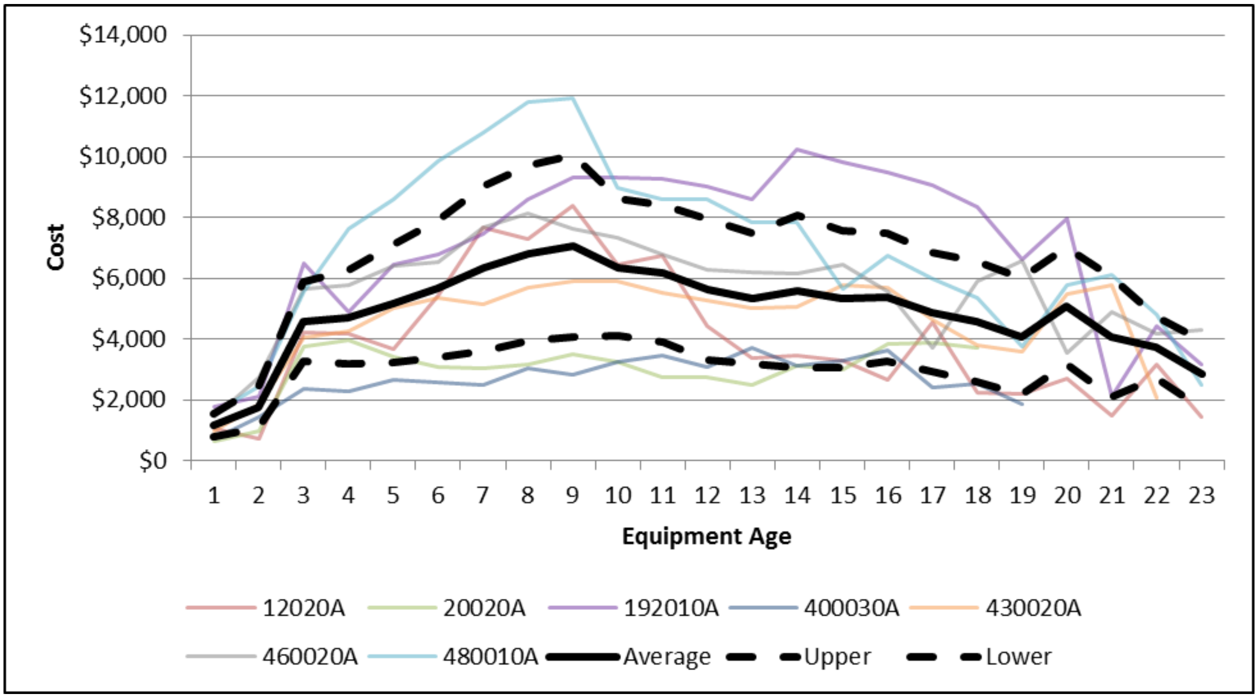


Figure 5.4 Adjusted Average O&M Costs for Select Light Duty Vehicles

Likewise, the analysis of select heavy duty vehicles revealed similar trends. Figure 5.5, below, illustrates the trend for seven selected heavy duty vehicles in terms of average O&M costs using the numbers as originally recorded. The graph again highlights the issue with high early O&M costs, although not quite as pronounced in the first year as with the light duty classcodes. It further illustrates how the trend peaks and, in this case, tapers off after about the 15-year mark. This trend is indicative of lower utilization of these vehicle types after about 15 years of age.

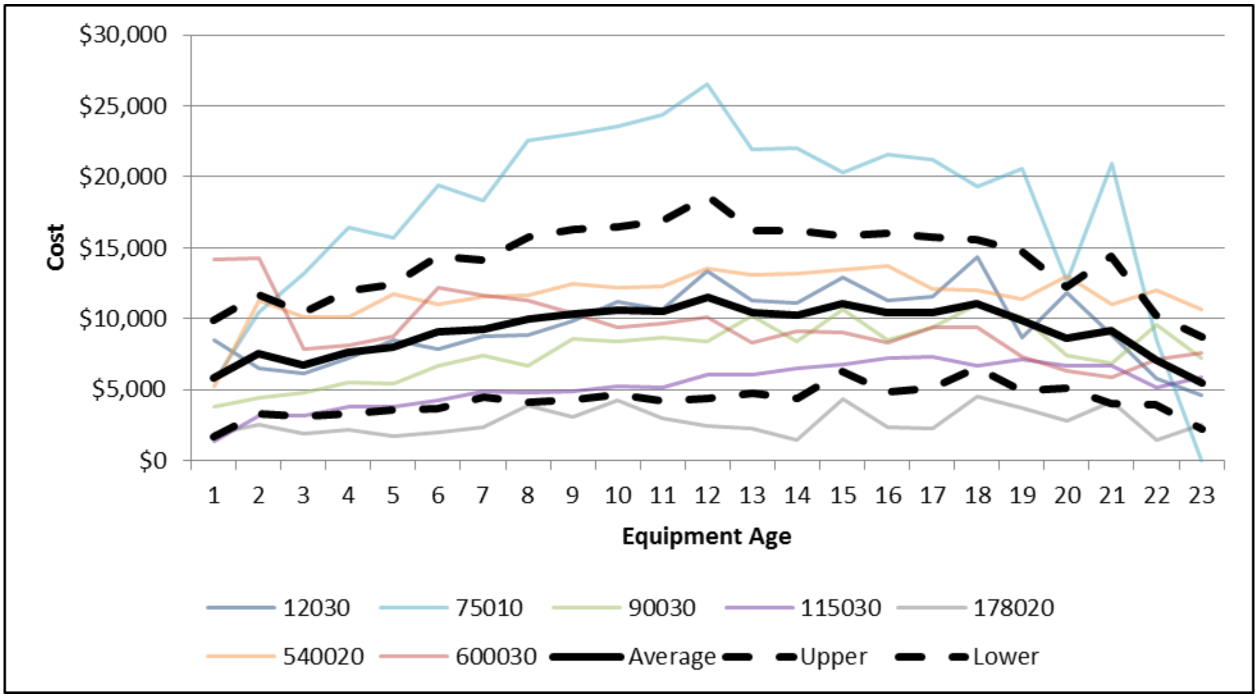


Figure 5.5 Original Average O&M Costs for Select Heavy Duty Vehicles

As with the light duty vehicles, the modification to the first two years of data yields a significant change in the early O&M cost numbers. Below, Figure 5.6 shows the trends for the same heavy duty vehicles in terms of average O&M costs using the adjusted values for the first two years, along with the updated down time rate. The sharp increase in year three can be clearly identified as the unadjusted O&M costs are significantly higher for the heavy duty vehicles. The sharp increase at this point is also contributed by the higher down time rate for heavy duty vehicles and more expensive repair costs, no longer constrained after year two.

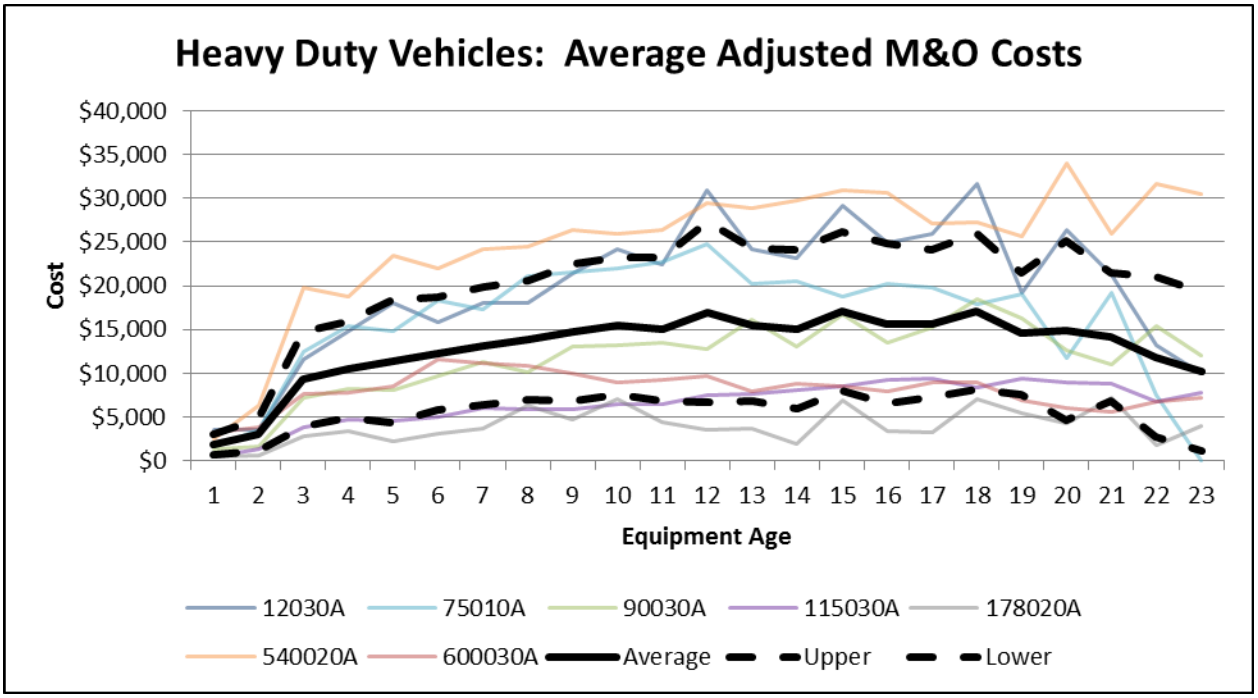


Figure 5.6 Adjusted Average O&M Costs for Select Heavy Duty Vehicles

Per approval from TxDOT fleet management personnel, the described modifications to the O&M costs, including down time rate adjustments, were incorporated into the software and the cost forecasts were updated accordingly. After implementing these changes, the results of the ERO process were reviewed for all of the classcodes. As part of this evaluation, several issues were evident from the software's replacement recommendations. Therefore, an in-depth review of the O&M cost forecasts was subsequently performed.

5.3.3 Solutions Identified

The original strategy for forecasting the O&M costs developed for project 0-6412 depended on the use of SAS, as initiated by the graphical user interface (GUI), to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast equipment O&M costs for two different strategies: cost current trend and cost equal mileage.

For the cost current trend model, the historical data for annual O&M costs are averaged over all vehicles of a certain age within a classcode and modeled versus the independent variable, equipment age. The resulting model is used to forecast O&M costs for the 20-year horizon. The cost equal mileage strategy involves taking the annual O&M cost total and dividing it by the unit of utilization, miles or hours, for each vehicle. This O&M cost rate is then averaged for all vehicles of a certain age. Once averaged, a statistical model is generated for the average cost rate versus equipment age. In addition, the utilization values are averaged over all vehicles in a given classcode for the most recent year of operation recorded in the database. The average O&M cost rate generated by the model is then multiplied by the average utilization value to provide the forecast for each year in the horizon based on the equipment's age. For both of the O&M cost forecasting strategies, the SAS macro source codes were developed to generate the following five different types of models: 1) Linear Model; 2) Polynomial Model; 3) Logarithm Model; 4) Exponential Model; and 5) Power Model.

The SAS macro also has the capability of running through all of the linear and nonlinear models and automatically identifying and selecting the best-fit model, per the highest R-squared value, for forecasting the O&M costs (based on equipment age) for any chosen classcode. The objective was to use SAS to create and select the best-fit model for the data and incorporate that model for forecasting O&M costs into the optimization engine. For more information about the development of these models and the selection process, see Fan et al. (2011a, 2011b).

Through an in-depth evaluation of the software results, it was discovered that the O&M cost forecasts for a number of the classcodes was unduly influencing the keep/replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that, in some cases, yielded negative O&M costs for future years. The evaluation of the quality of the fit (R-square value) for the model options led to the software program choosing non-linear models for nearly all of the equipment classcodes. Due to the distribution of data for some of these equipment types, as a result of lower utilization as vehicles age, this resulted in a curvilinear model with a negative slope generated over the latter years of the lives of the equipment units, as illustrated below in Figure 5.7.

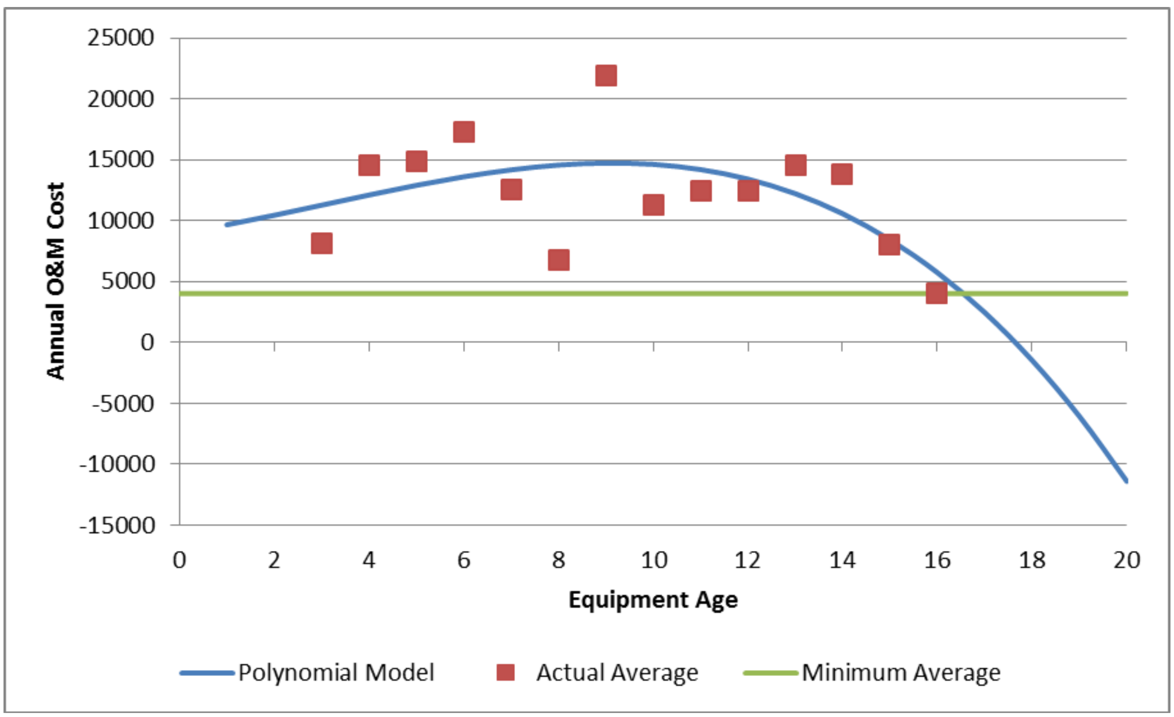


Figure 5.7 Graph of the Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 400020 (Light Duty Truck, 4-WD Pickup)

Note that Figure 5.7 shows the nonlinear model yielding a reasonable fit for the data; however, the slope of the model is negative after about year 10, an issue identified earlier, and would subsequently result in negative O&M costs as equipment in this classcode ages beyond 17 years. Therefore, the statistical models like this one result in lower projected O&M costs as vehicles age, and the tendency of the software to not recommend equipment replacement until the end of the horizon (20 years). It was determined that this would have an adverse impact on the ability of the optimization engine to appropriately generate recommendations for replacing equipment, as the decreasing trend as vehicles age is not consistent with expectations. However, it is based on the data available and a countermeasure has been developed to account for this issue.

The problem with lower utilization may be corrected in the future as new data is implemented, since the fleet has been right-sized. Therefore, making changes to the models themselves was not a recommended solution for this issue. Instead, it was determined that a minimum, annual O&M cost value be established for the forecasts based on the available data. It was determined that the model process should be completed and any negative forecasted value be replaced with the minimum value. That value has been determined to be the minimum, annual average O&M cost found in the data across the available equipment ages. This value is illustrated in Figure 24 as the “Minimum Average.” Note that in this particular case, no O&M cost data exists for vehicles older than 16 years of age, so the minimum for equipment aged 17 to 20 years, must come from an earlier value (i.e., age 16).

Several additional strategies were also discussed, and presented to TxDOT personnel (progress meeting August 16, 2012), including the use of a percentile value (e.g., 10th percentile O&M cost) as the minimum or an experience-based value determined by fleet management personnel due to familiarity with typical O&M costs incurred for keeping equipment operational. Nonetheless, it was determined that using the minimum average calculated by the software, per the data entered and updated each year, be utilized. It was further determined that the minimum values calculated by the software be provided to TxDOT for review and approval. It was also recommended that in these instances, a warning message, or some similar indication, be provided by the ERO software to alert the user that an issue with negative forecasted values was detected upon running the optimization, and that the software was proceeding with the minimum value calculated for that classcode.

Establishing a minimum value for O&M cost forecasts has been found to solve another, similar issue found in the data. It was determined that some of the forecasting models were beginning with negative values due to the lower adjusted O&M costs established for the first two years of operation, per the aforementioned modification in Section 5.3.2. Below, Figure 5.8 illustrates this type of trend as identified for classcode 90040.

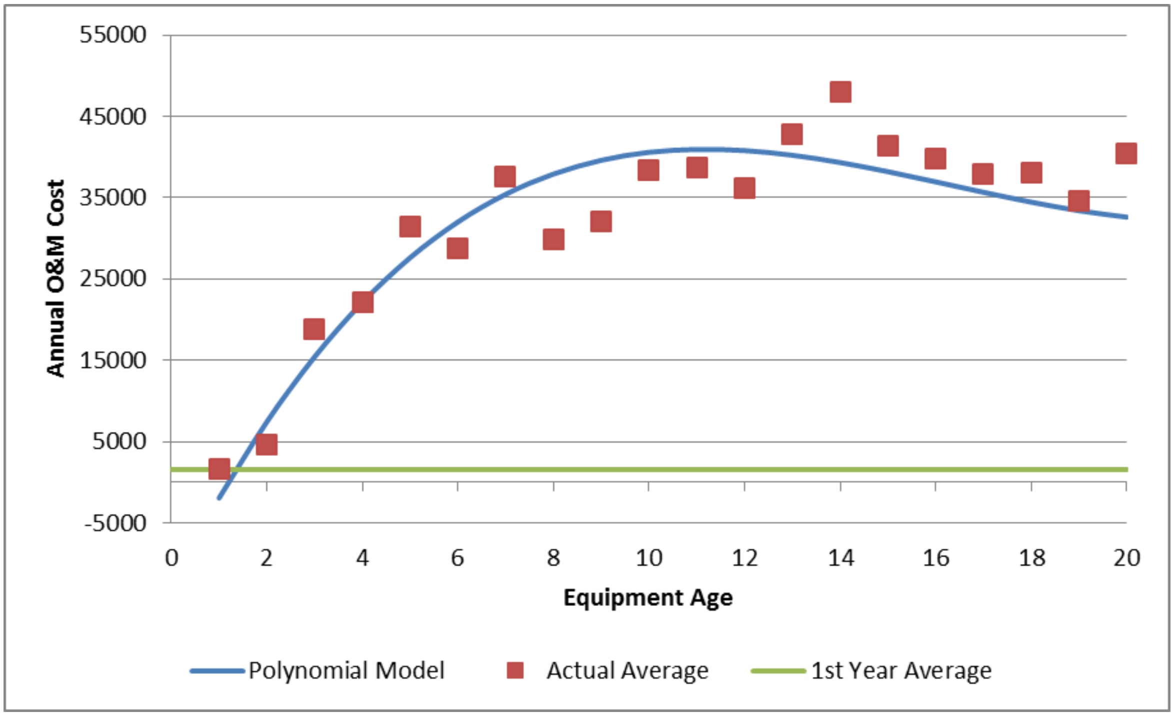


Figure 5.8 Graph of the Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 90040 (Grader, Motor, Class IV)

While Figure 5.8 shows a decreasing trend in O&M costs as vehicles age past about 12 years for this classcode, the problem with negative forecasted values appears at the beginning of the life-cycle. Again, a minimum O&M cost value could be used to solve this issue, but in this case, data exists for the year where the model dips below zero. Therefore, the data for that year could be used to establish the minimum. As such, the strategy for calculating a minimum was modified. First, the software is tasked with finding the average O&M cost from the data for the age value where a negative cost has been forecasted, as shown in Figure 5.8, and to use it if one exists. If none exists, the software is to instead use the minimum average O&M cost calculated from the remaining years available in the data, as mentioned above and illustrated in Figure 5.7. This two-part strategy will be implemented to solve the issue with negative forecasted O&M costs.

Another issue was identified in the review of the TERM data. The method for establishing the cost equal mileage forecast, as identified above, involves the calculation of an O&M cost rate for each vehicle based on the utilization. However, if the data indicated that no O&M costs were incurred, or no utilization was recorded, then this rate is effectively zero. Therefore, these entries yield no measure of O&M cost for aiding in the creation of the forecasting models for this strategy. It was determined that each equipment unit in the fleet is at least inspected annually and thus, acquires a minimal maintenance cost. As such, a minimum O&M cost rate will again be established for each of these classcodes based on the existing data (i.e., the minimum O&M cost rate for a vehicle of the same age) and assigned to any vehicles with an otherwise zeroed out O&M cost rate. These values will be established using the SAS code and implemented in the development of the O&M cost forecasting models for the cost equal mileage method.

Another issue identified with the creation of the O&M cost forecasts, was that the statistical model fits for the chosen models were not always good. The model selection methodology is based on the model with the highest R-squared value being chosen for the established forecast. However, this does not guarantee that a model with a high-quality fit will be chosen. For example, in Figure 5.7, the polynomial model chosen as the best fit has an R-squared value of 0.33. As such, in a similar manner to the model selection process for the purchase cost forecast, a threshold R-squared value was chosen as a check against the quality of the fit. The value chosen was 0.5, and if no statistical model can be fit to the data with a higher quality than that threshold, then a default option is to be utilized.

The default option for forecasting the O&M cost is to use the average O&M cost for each equipment age value based on the historical data available for an individual classcode. The purpose of this strategy is to provide a fail-safe to ensure that historical data is utilized in the forecast of O&M costs, even if a high-quality model cannot be generated, and only relatively high-quality models be used for forecasting O&M costs. Regardless of the forecasting strategy implemented, TxDOT personnel requested that the GUI provide a warning message to the user when the statistical models fail to generate a model exceeding the R-squared threshold, and regardless of the result, the output Excel file for the O&M cost forecast provide the highest R-squared value achieved (per meeting on August 16, 2012). The established threshold will also prevent issues found with some power and exponential models. When these types of models are chosen as having the best fit for the existing data, they often have the tendency to forecast some counterintuitive results, particularly in the tail ends of the model.

It was found that when exponential and power models are chosen as the best fit for forecasting O&M costs, it is often due to outliers in the data. For some classcodes, only a couple of vehicles (sometimes only one) will be found in the database for a particular age value. This happens most often for vehicles over 15 years of age. If a relatively small sample is available for a specific age, really expensive O&M costs for even one vehicle can have a substantial impact on the average, and thus, unduly influence the statistical model chosen to fit the overall data. An example of where this occurs is shown in Figure 5.9, below.

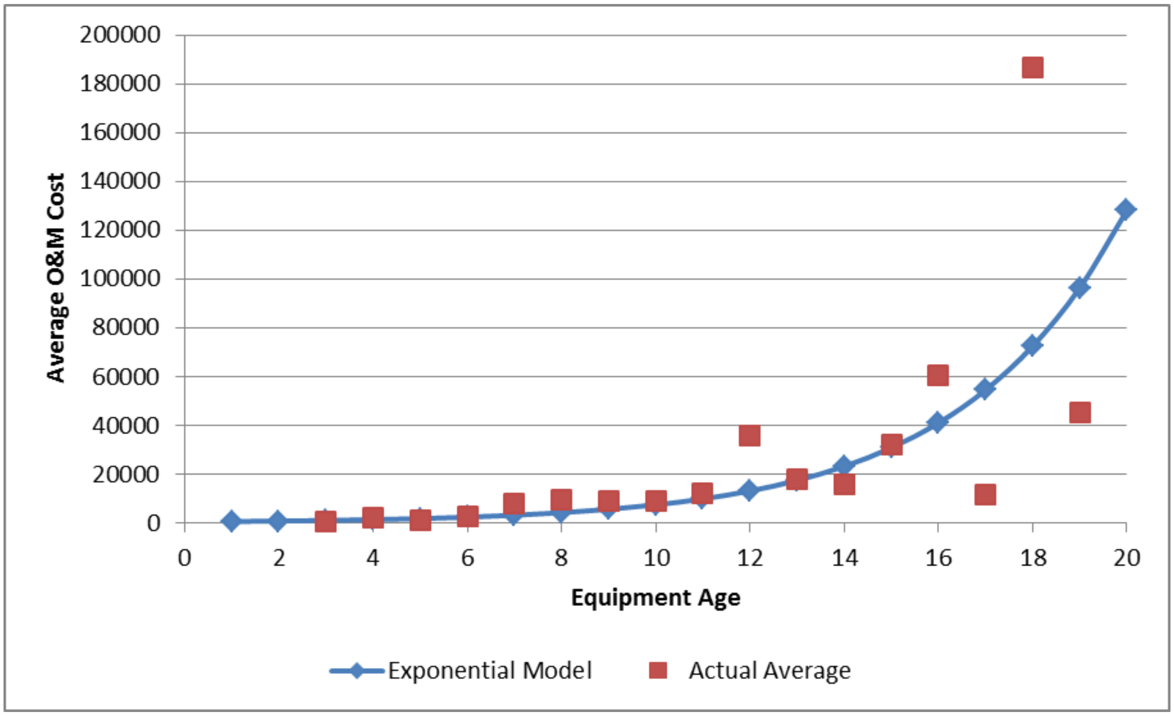


Figure 5.9 Graph of the Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 520020 (Truck, Conventional Dump)

As can be seen in the above graph, the average O&M cost for a vehicle aged 18 years old is noticeably higher than 17 or 19. This is due to the extremely high O&M cost recorded for a single vehicle in this category. It should be noted that this model was created for the cost equal mileage methodology. Therefore, an O&M cost rate was calculated and then multiplied by the average utilization for all vehicles for this classcode from the most recent year. Since this vehicle is old, the actual utilization was far lower than this average, but the methodology based on equal utilization inflates the forecasted O&M cost. As such, the statistical model chosen was an exponential model with an increasing O&M cost with equipment age that spikes near the end of the horizon. This forecast yields substantially high O&M costs for equipment beyond 17 years of age. It was determined that the removal of this, and other similar outliers, might be extremely helpful in the model generation process.

It was decided, along with input from TxDOT personnel, that these outliers be removed using an outlier removal process similar to that implemented into the SAS code for the purchase cost forecasts. In addition to the SAS macro based data cleaning process, this outlier removal procedure will be initiated as part of the algorithm to eliminate major outliers from the data before the statistical models are created by the software. To see more information about the SAS macro based data cleaning process involving the first outlier treatment, see Fan et al. (2011b). In the second round of the outlier removal process, specifically for average O&M cost values, upper and lower thresholds are created for a range of acceptable values. Those thresholds are calculated based on the lower and upper quartiles (Q_1 and Q_3) and the subsequent interquartile range ($IQR = Q_3 - Q_1$) as follows:

$$F_1\ (lower\ threshold) = Q_1 - [2 * 1.5 * (Q_3 - Q_1)]$$
$$F_3\ (upper\ threshold) = Q_3 + [2 * 1.5 * (Q_3 - Q_1)]$$

As such, average O&M cost values falling outside of the above thresholds are eliminated from consideration for the creation of the statistical models. It was also requested by TxDOT personnel that a warning message appears in the GUI identifying for the user when outliers have been removed from the model (meeting on August 16, 2012). The review process also determined that another issue exists for classcodes with small sample sizes.

In the process of evaluating the ERO software results for each classcode, it was found that the cost estimations were unavailable (i.e., zeroed out) for the entire 20-year horizon for approximately 10 classcodes. Further investigation of the issue revealed that this phenomenon involves classcodes where only one year of purchase cost information is available in the TERM database. If only one year of purchase cost information is available, a forecast cannot be generated; therefore, the optimization process is invalidated. It was determined that an update to the SAS code will be implemented to solve this problem.

Solutions to the aforementioned issues with the O&M forecasts and ERO results have been identified and the software is in the process being updated accordingly. The additional outliers will be removed from the O&M cost data and the minimum O&M cost values will be calculated for each classcode by the software. Furthermore, the statistical models generated will be evaluated against a minimum R-squared value. This threshold has been established for choosing between a statistical model and the historical average for forecasting O&M costs. With these, along with a few additional modifications to the SAS code to ensure a forecast is generated for all classcodes, regardless of sample size, the details for a software algorithm have been finalized.

5.3.4 Implementing a Software Algorithm

The process of implementing a software algorithm to resolve the issues with the O&M cost forecasts has been initiated. The identified software algorithm, as developed using SAS macro codes, is provided below in Figure 5.10.

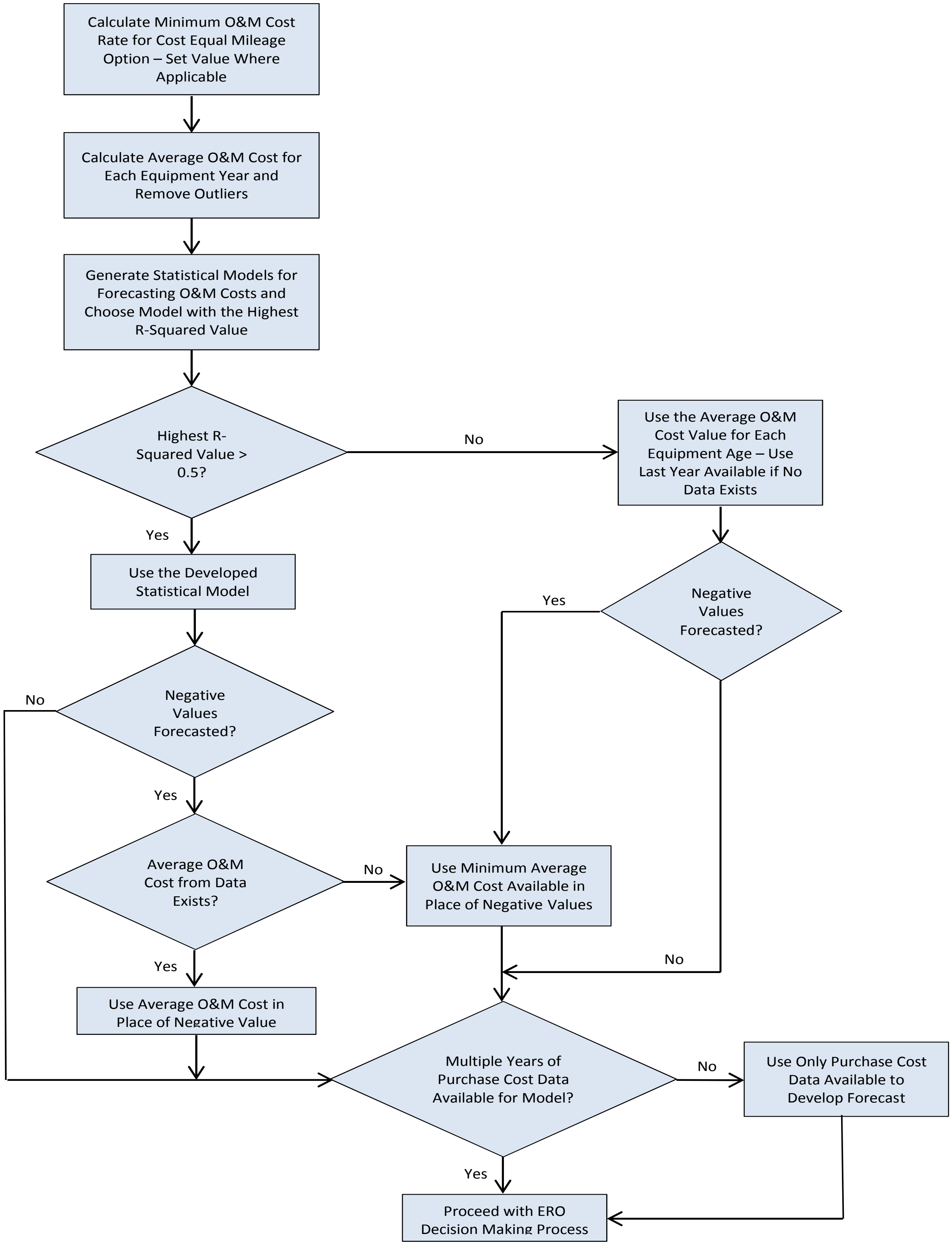


Figure 5.10 Flow Chart of the O&M Cost Forecasting Algorithm Software Implementation

As shown in Figure 5.10, the algorithm first calculates the appropriate average annual O&M values and removes any outliers across all equipment ages using the IQR method described in Section 5.3.3. Then, it creates the statistical models and chooses the one with the highest R-squared value. The software subsequently checks whether or not the R-squared value is great than 0.5. If the model passes the threshold check, the software then determines if any forecasted O&M costs are negative. If it fails the threshold check on the R-squared value, the forecast uses the existing average O&M values based on equipment age. If any forecasted values are negative from either method, the software uses the described process for establishing and utilizing a minimum annual O&M value. With the appropriate O&M forecast in place, the software checks for the availability of purchase cost data for creating a purchase cost model. If such data exists, a purchase cost model is created and the ERO decision is evaluated based on the appropriate forecasts. If a model cannot be generated, the available purchase cost information is utilized as the forecast, and the ERO process continues.

5.3.5 Reviewing the Results

In order to review the level of success achieved from applying the algorithm, the forecasted O&M costs for all of the classcodes will be thoroughly evaluated. The O&M cost forecasts will be checked for negative values, and the statistical models will be evaluated for quality of fit. Average O&M cost values will be reviewed to confirm that all outliers have been removed. Subsequent ERO results will be evaluated in the GUI, and any remaining issues will be resolved. It is intended that the software algorithm be developed and implemented such that all classcodes will generate appropriate forecasts and results, based on the best available use of the historical TERM data, regardless of sample size or other characteristics of the data.

5.4 Summary

The purpose of the task described in this chapter was to estimate down time costs unique to each equipment classcode in the Texas Department of Transportation (TxDOT) TERM database and investigate O&M costs coupled with TxDOT's recent fleet rightsizing efforts. As discussed in Section 5.2, the original strategy for estimating down time was to use one universal rate for all of the classcodes. However, this estimate was limited, as vehicles from different classcodes are likely to result in distinct costs associated with being unavailable. Therefore, a unique rate was established for each individual classcode based on techniques found from a review of relevant literature. Since down time is part of the overall O&M costs for each equipment unit, its proper estimation was a critical component in establishing forecasts for O&M costs.

Based on the TxDOT TERM data, the research team developed five different types of models (including Linear/Polynomial/Logarithm/Exponential/Power models) in TERM2 as a result of project 0-6412 to forecast O&M costs using equipment age as the independent variable. It was found that the strategy for forecasting the O&M costs required some modifications. Upon implementation of the original strategy, some forecasted O&M costs were found to be much higher or lower than expected, and in some extreme cases, negative. Early replacements were being recommended as part of the ERO results, and other issues were noticeable from a full review of the forecasts for each classcode.

One of the issues identified included high, early O&M costs across many of the classcodes. An appropriate strategy was developed and approved for modifying the first two years of cost data prior to being utilized for generating statistical models. Another issue found was the forecast of negative O&M costs based on the statistical models. It was determined that replacing these negative forecasts with minimum, annual O&M cost values, calculated from the historical TERM data, would be appropriate for resolving this problem. Furthermore, it was determined that establishing a minimum O&M cost rates would be necessary for populating missing entries (due to zero O&M costs or utilization recorded for specific vehicles) for the cost equal mileage option.

In addition, as part of the statistical model generating process, establishing a minimum threshold value for R-squared to control for the chosen model's goodness-of-fit, along with a second outlier removal process, were necessary for improving the accuracy of forecasted results. Lastly, it was found that minimal sample sizes within the data, including that for purchase cost information, would need to be accounted for in the establishment of forecasted costs as this has a substantial impact on the ability of the optimization engine to provide cost comparisons and appropriate keep versus replace decisions. It should be noted that the aforementioned strategies for improving the O&M cost forecasts are in the process of being implemented into SAS and comprehensively tested and validated.

Chapter 6. Survey of Fleet Management Practices During Emergency Situations

6.1 Introduction

Texas is a state that faces many potential disaster situations. Frequent natural disasters in the state include hurricanes and wildfires, as well as other forms of severe weather. In addition to these scenarios, Texas has to face the possibility of manmade disasters ranging from nuclear meltdowns to terrorist attacks. In light of these concerns, TxDOT is focusing on maintaining a robust fleet to meet its requirements to DPS and Texas DEM. TxDOT also wishes to provide as much assistance as possible to the citizens of the state of Texas. However, the fact that TxDOT has a fleet valued at $500,000,000 with an annual turnover rate of $50,000,000 has motivated TxDOT to 'right size' its fleet. This right sizing will optimize the equipment replacement purchases, potentially saving the state of Texas, and taxpayers, hundreds of thousands of dollars a year. However, as future funding levels become more uncertain, the lack of available funds necessary for optimal vehicle replacement is very likely. This raises several issues, including the necessity to determine the potential impacts of future uncertain equipment purchase costs. However, as the availability of funds decreases, TxDOT is interested in determining how this limitation will affect purchasing and fleet robustness. A level of robustness is needed in order to respond to two simultaneous disasters. In order to evaluate if this level of robustness is met, TxDOT must list its levels of commitment to DPS and DEM. The purpose of the task to be discussed in detail in this chapter is to list these levels of commitment from the perspective of fleet management, as well as to ascertain how uncertain equipment costs will affect future replacement decision making.

6.2 TxDOT Involvement in Emergency Situations

To begin listing levels of commitment to DPS and DEM, the types of disasters must first be identified. Texas, as of now, has disaster plans in place for hurricanes, nuclear fallout/radiological source contamination, hazardous material leaks, health and medical disasters and terrorist attack scenarios. These plans are discussed in varying detail in the Texas Disaster Recovery Manual (TDRM) and its various annexes (State of Texas 2005, 2006a, 2006b, 2006c, 2006d, 2006e, 2006f, 2007). These plans are vague, as each individual disaster can, and most likely would, be different from every other occurrence. However, for the sake of clarity, TxDOT's listed involvement is outlined below.

6.2.1 Radiological Emergency Management

TxDOT has no official duties as listed in the TDRM for radiological emergencies (State of Texas, 2005). Certainly TxDOT would be asked to offer assistance to help evacuate the local citizenry, similar to commitments for other disasters, if an evacuation is needed. In light of this, TxDOT will probably be asked to assist evacuations in similar ways as specified for hurricanes. This would consist of deploying barricades and signage, as well as light-duty vehicles. TxDOT's commitment to other aspects of radiological emergencies is less clear. To the best of the researchers' knowledge, there are no specific plans for handling radiological disasters that list levels of commitment to the state. Also, because TxDOT's fleet specifications have not been supplied and are not readily available on the internet, TxDOT will have to review its fleet capacity and determine which vehicles would be most likely needed in any recovery efforts. These vehicles would be candidates for additional deployment as part of TxDOT's involvement.

6.2.2 Hazardous Material Leaks

Under subsection (F) of Section 26.264, Texas Water Code (State of Texas, 2010c), TxDOT allows its equipment and personnel to operate under the supervision and jurisdiction of the Texas Commission on Environmental Quality and the EPA. It offers these resources in order to assist in waste removal and cleanup. Not all TxDOT personnel are trained for hazardous material cleanup and containment; therefore, this level of commitment does not apply to untrained, unqualified, or unprepared resources (State of Texas, 2006b). Also, due to the ambiguity of these levels of commitment, no specific list of materials or personnel required has been provided. Given the knowledge of TxDOT's commitments in other areas, TxDOT will most likely be involved in quarantining the area, as well as preparing any necessary evacuations. Any hazardous material leak substantial enough to be declared a disaster would have to affect a large area; i.e., an oil tanker spill in the Gulf of Mexico. In light of this information TxDOT's level of commitment could be considerable, potentially larger than for a hurricane response.

6.2.3 Health and Medical Disasters and Biological Terrorism

Micro-organisms, such as bacteria and viruses, cause many types of diseases all over the world. As a result of this reality, an epidemic in which a new strain of a disease sweeps across Texas is a constant possibility. In the case of this type of disaster affecting the state, TxDOT would be called upon to help in two ways. In the event of mass death of humans or animals as the result of the spread of a disease, the Public Works and Engineering division of DEM will assist in cleanup and disposal of remains and wastes (State of Texas, 2006c). The Public Works and Engineering department is headed by TxDOT and thus, TxDOT will provide its largest level of commitment to meet their needs. When considering fleet requirements, TxDOT would have to produce enough vehicles that are capable of transporting biomatter that is appropriate for the size of the disaster. Since a standard level of commitment is not specified in the literature, fleet managers will have to extrapolate a reasonable level of commitment from a working knowledge of the topic.

In the event of a biological disaster, TxDOT will also help implement control/quarantine measures (State of Texas, 2011a). These measures would effectively separate the healthy population from the infected in an attempt to safeguard the uninfected. In this capacity, TxDOT will be asked to provide traffic control devices such as cones, barricades, signs, and vehicles to manage and maintain the quarantine zone (State of Texas, 2007). The actual level of commitment to Texas DEM will vary greatly depending on the size of area impacted by the outbreak, the number of people/animals infected, and the speed at which the disease spreads.

6.2.4 Transnational Organized Crime

Although not technically a disaster, transnational crime could prove to be a significant problem to the state of Texas. Mexican drug cartels and other transnational criminal organizations have been disrupting parts of Mexico for years. Given the motivation of these organizations, mainly making profits, they have incentive to cross the border and try to expand their operations into the United States. Since the Texas-Mexico border is two thirds of the entire

US-Mexico border, there is a real threat of this crossover occurring in Texas (Texas Department of Public Safety, 2011).

In 2009, drug cartels took control of the city of Juarez, just south of El Paso. Approximately 6,000 people had been murdered in the previous year. It took a combined military and police force of 7,500 troops to take back the city and restore order (Webster, 2009). Given the size and scope of these events, and the clear motivation that the gangs have for pursuing profits in the US, it is conceivable that the violence might spill over to Texas.

If there is a spillover into the United States, it may happen that the DEM and DPS would be called upon to respond to the fallout. TxDOT, as a transportation agency, would obviously not be on the front lines of a response, but may be called upon to assist the state in other ways. Potential responsibilities, ranging anywhere from assisting in logistical operations to facilitating limited evacuations, should hostilities become that severe, could fall to TxDOT. As there has been no ‘invasions’ or hostilities of that severity inside the United States since the Civil War in the 1860’s, and there was no agency comparable with TxDOT at that time, no historical examples could be found to demonstrate what might be asked of TxDOT.

6.2.5 Hurricanes

Hurricanes are one of the most prominent and frequent major disasters to affect the state of Texas. Hurricanes are storms that can cover huge tracks of land with sizable rain quantities and high winds. These storms evolve from tropical disturbances that form in the Atlantic and move through the southern or east coast or the Gulf of Mexico. Nearly all Atlantic hurricanes follow this standard path. Any hurricanes affecting Texas will arrive from the Gulf of Mexico and move inland from the point of landfall. Most storm systems come and go without major impacts to the state of Texas, but about every few years a powerful storm will affect the state. Notable hurricanes to affect the state in the past decade include Bret, Claudette, Rita, Humberto, and Ike (State of Texas, 2010c). Due to the large amount of rain dropped by these storms, a hurricane disaster in the Gulf Coast area could be accompanied by flooding disasters located in other areas of the state.

As a result of the dangers posed by hurricanes and there inherent unpredictability, the Texas DEM has established clear requirements for state agencies in the event of certain eventualities. Texas has divided up the state into five hurricane disaster districts, which include 2A, 2B, 2C, 3A, and 3B (All of these listed disaster districts are described later in this section). All of these districts are located along the coast and altogether do not cover the entire state. Each disaster district has its own evacuation plan in place with its own level of TxDOT support, as will be shown later in this section. TxDOT is mainly responsible for helping traffic flow in these districts by setting up road barricades and signage along the contraflow routes. An example of this level of commitment can be illustrated using district 2A, as shown in Figure 6.1 below.

A	B	C	D	E	F	G	H
Surge	**Evacuation Corridor**	**Secondary Street Junction**	**Latitude**	**Longitude**	**Officers**	**Map Point**	**Vehicles**
Zone A	ST HW 288	SH 332E at FM 523	95° 20' 14.28" W	28° 58' 54.60" N	-	844	Static Traffic Control Device
Zone A	ST HW 288	FM 523 at FM 2004	95° 22' 50.80" W	29° 7' 8.71"	-	843	Static Traffic Control Device

I	J	K
Control Device	**Instructions**	**Source**
Control Device	Appropiate number of reflectorized traffic cones to establish (2) traffic transitions in conjunction with arrowsticks on Law Enforcement Units to force turn all SH 322E W/B traffic onto FM 523 N/B, and force all FM 523 N/B traffic into the inside lane south of SH 332E.	TMP District 2A - Sub 2A
Control Device	(2) Class III Reflectorized Barricades with Road Closed Signs to close FM 2004 N/B north of FM 523.	TMP District 2A - Sub 2A
Control Device	Appropriate number of reflectorized traffic cones in conjunction with an arrowstick on a Law Enforcement Unit to force flow all SH 332 W/B traffic onto SH 288 Bus N/B.	TMP District 2A - Sub 2A

Figure 6.1 Examples of TxDOT Levels of Commitment (District 2A) (State of Texas, 2010d)

Figure 6.1 shows that levels of commitment come in the form of assisting evacuations. This information is taken from the contraflow manual for district 2A and has been altered from its original form. For illustration purposes, the information has been transferred to an Excel spreadsheet. Most of the level of commitment is in the form of barriers and signage for traffic control. In the manual for disaster district 2A, a disaster scenario for a specific location, with the coordinates listed, is provided with a complete description of appropriate procedures. The format for displaying information is different for each disaster district, but typically the same type of information is presented. The only deviance from this style is for district 3A.

The level of commitment required is not a major concern for fleet management personnel because it only includes traffic control, and both the type and number of vehicles that would be needed to deploy the equipment are not specified. TxDOT will have to determine the fleet capacity needed to implement this plan and use that as a specified fleet commitment.

Disaster district 2A includes Brazoria, Galveston, and Harris counties. The main evacuation routes out of this district include State Highway 288, State Highway 35, State Highway 36, State Highway 332E, FM 2611, and State Highway 6 in Brazoria County. In Galveston County, the evacuation routes consist of Interstate 45, State Highway 6, State Highway 87, State Highway 146, and FM 2351. The evacuation routes out of Harris County include Interstate 45, State Highway 6, State Highway 146, State Highway 288, Interstate 10, US Highway 59, State Highway 290, and State Highway 225. This disaster district is unique in that it is the most densely populated due to the inclusion of Houston in Harris County.

Disaster district 2B contains Angelina, Chambers, Hardin, Jasper, Jefferson, Liberty, Nacogdoches, Newton, Orange, Polk, Sabine, San Augustine, San Jacinto, Shelby, Trinity, and Tyler counties. The primary evacuation routes out of the district are US Highways 59, 69, 96, 90, 287, 190, 259, State Highways 105, 82, 87, 73, 347, 146, 321, 21, 62, 12, 19, 124, and Interstate 10. This disaster district covers 16 counties and most of southeast Texas. A possible complication for evacuation efforts comes from its close proximity to the Louisiana border. If a hurricane threatened both Texas and Louisiana simultaneously, it is possible that the road systems might have to deal with more evacuees than just Texas residents. This should be taken into account when preparing for a disaster in this area.

Disaster district 2C covers eight counties including Austin, Colorado, Fort Bend, Matagorda, Montgomery, Waller, Walker, and Wharton counties. Evacuation routes consist of Interstate 45, US 59, US 290, State Highway 6, State Highway 36, and Interstate 10. It mainly consists of the coastal section of Texas, west of district 2B, excluding Harris, Galveston, and Brazoria counties.

Disaster district 3A has a notable level of TxDOT commitment for emergency services. These commitments pertain to the contraflow configuration of a few major evacuation routes; US 77, US 83, US 281, and SH 100. The district covers Cameron, Hidalgo, Jim Hogg, Starr, and Willacy counties. Therefore, the TxDOT commitment levels discussed here only focus on the road sections that lie in these counties. If contraflow movement was implemented on all of these highways combined, they would result in a TxDOT commitment of 41 units (State of Texas, 2010d). A unit is described as a vehicle and accompanying personnel. Similarly, in disaster district 3C, 18 TxDOT units are needed to maintain closures of ramps (State of Texas, 2010e). In all districts, TxDOT is required to produce, place, and recover signage and barricades to aid in channelizing traffic. These signs/barricades range from type III barricades to message boards along the evacuation routes (State of Texas, 2010f).

Disaster district 3C covers the Corpus Christi area. More specifically it is made up of Aransas, Bee, Brooks, Duval, Jim Wells, Kenedy, Kleberg, Live Oak, McMullen, Nueces, Refugio, and San Patricio counties.

TxDOT would be required to supply vehicles for both the evacuation and recovery efforts. Heavy equipment, such as dump trucks, bulldozers, backhoe loaders, aerial work platforms, and forklifts, to name a few, would need to be made available for use by the emergency relief teams. So far, no specific requirements from the DPS or DEM have been found for these types of vehicles. Despite this fact, if the governor or emergency manager made a request for specific equipment, then TxDOT would be required to have a reasonable number available and in working order.

Many historical resources can be examined to estimate the levels of commitment for TxDOT as part of hurricane response. Attempts to find such information through Google.com and other internet sources have proven fruitless. When browsing these resources, the available information is more applicable for policy makers or similar individuals, and is not relevant to fleet management.

6.2.6 Floods

In addition to the aforementioned disasters, Texas must also deal with floods in low-lying areas of the state. As most know, floods occur when water accumulates in an area faster than it can be removed. In most parts of Texas, water is removed by a system of natural flow channels, such as creeks and rivers, and by the ground absorbing the water. In cities, this natural flow process is often stymied by manmade structures. The profusion of concrete prevents water from being absorbed by the ground. To alleviate this problem, many municipalities build drainage systems in the form of man-made canals and water reservoirs. The problem with these systems is that they are only made to withstand a certain amount of water; when their capacity is exceeded, homes, businesses, and other personal property, as well as lives are put at risk (State of Texas, 2006e).

There are many examples of this type of disaster striking Texas. A short list would include: the flood of 1935 (Aquifer, 2012) , flooding in 1984 (FEMA, 1984), and flooding in 2001 (FEMA, 2001). (This list does not include the three worst floods, but is created to provide a sampling) The Houston, Dallas-Ft. Worth, and Austin to San Antonio urban sectors have the most potential for flood impacts, along with other scattered flood zones. These three main zones would be the most problematic for disaster relief because of the high density of life and property. The state of Texas has no formalized plan of action listed under the State Emergency Management Plan (Texas DEM, 2012). This means that levels of commitment for TxDOT have not been established. TxDOT would be called upon to help in any way possible, to be sure, but requests would be made based on equipment and personnel availability before the storm.

6.2.7 Wildfire

The state of Texas routinely faces threats from wildfires. A recent example of this would be the 2011 wildfires that burned 34,356 acres(Bastrop County Complex fire, 2012). The wildfires lasted for 37 days and accounted for 47.3% of all the wildfires in the United States for that year. Given that much of Texas is dry and semi-arid, wildfires can happen quite frequently. In addition to the 2011 fires, Texas has also experienced several other disastrous fire seasons, although none compared with the 2011 fires. As a result of the threat of wildfires, Texas DEM has created an annex to the State Emergency Management Plan to specify agency responsibilities during a fire disaster.

TxDOT's level of commitment to the DEM in this situation would be to provide fueling, water supplies, heavy equipment, and transportation in support of operations (State of Texas, 2011b). Possibly due to the unpredictable nature of these fires, and the variable severity, an exact list of requirements was not formulated. Despite this fact, TxDOT can be sure that the DEM will request, for a very severe disaster, all available equipment. This is of particular interest to a fleet manager because he/she would be responsible for meeting these requests. TxDOT should analyze previous requests, especially for the 2011 wildfires to estimate the number and type of equipment needed to meet the commitment levels.

6.2.8 Earthquakes

Although not known for it, Texas is capable of experiencing earthquakes. Fault zones run across the state from the southwest to the northeast and include the Luling, Balcones, and Mexia fault lines (American Association of Petroleum Geologists, 1945). Although mostly geologically inactive, they still pose a potential threat. This was demonstrated by the recent earthquakes in East Texas. A 4.3 and a 3.9 tremor struck the area around Timpson, TX, in May of 2012 (London, 2012). Although these earthquakes did little damage and caused few casualties; the fact that they did occur is of concern.

Although unlikely, if a major earthquake were to occur, then TxDOT would surely be called to help in the recovery efforts. In response to the 4.3 tremor on May 17, 2012, TxDOT checked roads and bridges in the area to ensure that no significant damage was done [30]. Any damage was likely minimal and required very little repair, but that might not be the case for a larger magnitude quake. The location of the quake also influences the severity. If the earthquake affects a more densely populated area than a rural location, TxDOT will then have to inspect and repair more infrastructures. TxDOT would also be likely called in to help clear debris and assist with the rescue of trapped victims. Fortunately, this is not a frequent occurrence for Texas; however, this also means that very little attention has been given to earthquakes.

6.2.9 Generic Evacuations

One of TxDOT's responsibilities during evacuations is fuel supplies. Recent disasters have shown that TxDOT needs to have a specific number of refueling trucks available to assist motorists that have run out of fuel during disaster evacuations. One disaster that demonstrated this clearly was hurricane Rita in 2005. Hundreds of motorists were stranded after they ran out of fuel. These stranded motorists presented a very serious traffic flow problem (Eskovitz, 2006). This would be a problem not only for hurricanes, but whenever a large population is evacuated at one time. In fact; this could be an even bigger problem for other types of disasters. For instance, if a sudden and wide-ranging disaster stuck a major city, then Texas would face massive evacuations without very much warning. An example of this could be a terrorist attack on Comanche Peak Nuclear plant, which lies just 40 and 60 miles away from Ft. Worth and Dallas respectively. If this was to occur, then massive evacuations of these cities and the surrounding metroplex would place a tremendous burden on the infrastructure currently built and would stress it to the point of failure. Once failure occurs and there is no longer enough gasoline to fuel the evacuations, vehicles will begin to stall. At that point, TxDOT would have to have enough refueling trucks to assist DPS and DEM in refueling operations in an attempt to keep traffic flowing smoothly. As discovered with Hurricane Rita, not only would these fuel trunks need to be available, but they would also have to be properly outfitted to handle normal passenger vehicles (Eskovitz, 2006).

Large numbers of vehicles would not only stop at refueling tankers, but for other circumstances as well. As stated in the hurricane response plan, TxDOT is required to implement short-term solutions to relieve congestions on evacuation routes. In order to do this, TxDOT would have to have a suitable number of tow trucks, traffic control devices, and device-deployment vehicles (State of Texas, 2010f). These traffic control devices are supplementary to the devices used to maintain contraflow lanes.

As previously stated, during a disaster TxDOT is primarily responsible for maintaining "Public Works and Engineering" (State of Texas, 2004). Once a situation has been classified as Escalated Response Conditions, then all agencies involved are ordered to, "Mobilize and deploy agency resources based on state approved requests for emergency assistance" (State of Texas, 2006f). This is interpreted to state that TxDOT and supporting agencies are required to render assistance on an as needed basis. There are no concrete procedures set in place since there are too many scenarios to properly plan for in such detail. Thus, these documents do not give adequate descriptions about fleet needs for disaster recovery.

TxDOT is also responsible to provide mobile communications support, to operate the TxDOT emergency radio network, and to provide 24-hour emergency radio support (State of Texas, 2006d). Again this does not specify a list of commitments to DEM, and it is implied that support will be given on an as needed basis. With respect to communication assistance, the Department of Information Security is the primary agency involved, and TxDOT provides assistance to them as required.

Another responsibility during an evacuation is the management of comfort stations. These stations are designated to service school buses, and other short range buses, that do not have the capacity to travel long distances on their own. TxDOT is assigned the responsibility to both set up and operate these stations (State of Texas, 2010f). In addition to services rendered for vehicles, assistance must be made available to passengers. This assistance will consist of food, water, shelter, and medical assistance. The medical assistance will be supplied from local sources (State of Texas, 2006e). It is not made clear in either the hurricane response plan, or in annex E, if assistance will be given to motorists traveling by car and other public transportation. TxDOT will have to clarify this in order to determine the number of resources to commit to these comfort stations. Although TxDOT is the lead department operating these stations, other organizations will provide assistance to them. This has been determined from the associated terminology, including “manage” and “assist in the set up and operation” (State of Texas, 2010f, 2006e). From a fleet management perspective, this suggests that TxDOT will be providing personnel and managing logistics of this operation within the department’s capacity, but any requirement that TxDOT would be unable to meet will be handled by other agencies.

6.2.10 Other Emergency Considerations

TxDOT is part of the Animal Resource Team (ART) and is required to work with the Texas Animal Health Commission (TAHC), Texas Department of Agriculture (TDA), Texas Commission on Environmental Quality (TCEQ), Texas AgriLife Service (ALEXT), Texas A&M University’s College of Veterinary Medicine (CVM), Texas State Animal Resource Team (TXSART), and in cooperation with unspecified industry stakeholder organizations. These organizations are put together to form an Incident Management Team (IMT). This team is subdivided to handle two tasks: one is to assist with large animals/livestock situations and the other involves household pets/companion animal issues. TAMU-CVM will assist with both subgroups. TxDOT is included in the first subgroup, which is responsible for the care of livestock and other large animals (State of Texas, 2010f). TxDOT is also responsible for assisting in the sheltering of animals, including pets, in the case of an evacuation. This would be achieved by posting signage with information about where shelters are located, as well as supporting the function of rest stops/shelters (State of Texas, 2010a). From a fleet management perspective, no specific vehicle requirements were listed in the relevant articles.

Rapid Response Task Forces are designed to respond to any disaster situation that arises in the state of Texas. There are both regular and light sized task forces. TxDOT is included in the composition of these task forces and is responsible for providing initial damage assessments following a disaster. These damage assessments include information pertaining to the “movement of personnel, equipment and/or goods in support of emergency operations.” For both the regular and light task forces TxDOT is responsible for providing a vehicle, as well as a single representative. (State of Texas, 2010b) It is not specified how many of these task forces will be called upon, but it can be assumed with reasonable accuracy that in the event of two simultaneous disasters, multiple task forces would be mobilized, especially if the disasters cover a large land area. TxDOT may also be asked to help send heavy equipment to assist in the cleanup of any blocked roadways that the task forces may find.

6.3 Survey of How Other State DOTs and Major Metropolitan Governments Provision their Fleets to Handle Multiple Disasters

Texas is a state that faces many potential disaster scenarios. The more frequent natural disasters affecting the state include hurricanes and wildfires, as well as other forms of severe weather. In addition to these, Texas confronts the possibility of manmade disasters ranging from nuclear meltdowns to terrorist attacks. In light of these concerns, TxDOT is focusing on maintaining a robust fleet in order to meet its requirements to DPS and Texas DEM. TxDOT also wishes to provide as much assistance as possible to the citizens of the state of Texas in the event of several simultaneous disasters. In order to accomplish this goal, TxDOT's fleet needs to be properly outfitted to handle these disasters. Therefore, the research team was tasked with determining how other state DOT's and major metropolitan governments provision their fleets to handle multiple simultaneous disasters. This was accomplished through the use of a survey distributed via email. The results were then compiled and formulated to allow TxDOT to review other state DOT's approaches to handling multiple simultaneous disasters.

The purpose of the survey is to determine how other state DOTs equip their fleets to handle one or, potentially, multiple simultaneous disasters. The survey is divided into three main sections. The first is intended to obtain an overview of disasters that have required a response from the individual state DOTs. The purpose of the second section is to acquire more in-depth information about specific historical disasters that have involved DOT resources. Finally, the third section seeks to gain the perspective of the DOTs about fleet management during, and preceding these disasters. The survey was created using Qualtrics and distributed to the various DOTs via email using the EMTSP ListServ. A list of the specific state DOTs to be contacted was provided to the research team by the project director (PD), and the survey was distributed to the associated contacts at the beginning of July, then again at the beginning of October, 2012. A complete copy of the survey can be found in Appendix C.

6.3.1 Overview of Disasters

The first few questions in the survey deal with an overview of disaster scenarios. It is designed to give the researchers and TxDOT an indication of the types of disasters that responding DOTs face. This information is important because it can be used to sort the types of disasters identified and subsequent responses in a way that would be more helpful to TxDOT. This information can also be used to gain insight into the respondent's answers to the other parts of the survey. For instance, if respondent A claims that little is done to prepare for disasters in his/her state, and then TxDOT can look at his/her overview of disasters to determine if this lack of preparation is warranted. This capability could prove useful as a screening tool to weed out respondents who do not meet the level of commitment that TxDOT expects of itself.

6.3.2 Historical Data

This section is intended to identify the respondents' actions during real disaster scenarios with which they have been involved. This data will provide a real-world understanding of how fleet equipment has been allocated in the past, and what roles other state DOTs have played in real disaster responses. This section of the survey includes questions determining what types of emergencies have required DOT involvement, including examples, what roles they played in disaster recovery, and if any of these roles were unexpected or required a deviation from their emergency response procedures.

6.3.3 Fleet Management Perspective

In the last section, the survey respondents are asked about how they manage their fleet requisitions and how emergency preparedness plays a role in their decision making, and if they have any initiatives in place to modify their current methods. It is likely that in the near future, budget limitations could hinder both the fleet management initiatives in place and those planned for future implementation. In light of this possibility, the respondents are asked what contingency plans they have in place in case this situation occurs in the near future. The surveyors are then asked about the impact of disaster preparedness on decision making with respect to making fleet maintenance or size/requisition decisions. This includes the prioritization of disaster preparedness when making fleet management decisions, and how/if the DOTs use this process as an influencing factor when making decisions about fleet size and allocation of available resources. Increasing disaster preparedness levels is often an objective for any state DOT and the survey includes questions intended to determine how other state DOTs might be working toward this goal. Finally, the survey is used to identify if cost benefit analyses are being used by the respondents and if new techniques are being implemented in order to see how these practices are connected to disaster response involving limited budgets.

6.3.4 Results

The survey was sent out to all accessible state DOTs via a Qualtrics website link through the EMTSP ListServ (i.e., those state DOTs who have joined the EMTSP ListServ); the surveyors received five complete responses. This is not an adequate number in order to have a comprehensive report. Despite this fact, the research team completed the task of summarizing the available results in a way that would be most beneficial to TxDOT. Upon obtaining more complete information from the surveys, the research team will carefully assemble and compile all of the relevant information, which will provide a useful reference regarding the fleet management practice, emphasizing how TxDOT should provision their fleets to handle multiple disasters.

The research team had originally planned on dividing the responses into two categories; one for states that face similar disasters to Texas (hurricanes and fires) or that routinely respond to multiple disasters fairly often (California and/or Florida) and the other category being states that do not have similarities to Texas or frequently face multiple disasters. The only responses to the survey were from the states of Oregon, Kansas, Missouri, Nebraska, and Pennsylvania. Due to the types of disasters that frequently impact these states; they fall into the category of those that do not share similarities with Texas.

DOT representatives from all of these states reported similar findings in the section covering an overview of disasters. All respondents reported winter storms and floods as major concerns. The specific results, with respect to overview of disasters, for each respondent can be seen below in Table 6.1.

Table 6.1 Overview of Disaster Results from Survey of Fleet Management with Respect to Multiple Disasters Scenarios

State	Disaster	Frequency	Avg. Severity
Pennsylvania	Flood	1-3	Minor-Average
	Winter Storms	6-20	Minor-Average
Oregon	Fire	1-3	Minor-Average
	Flood	1-3	Minor-Extreme
	Epidemics/Biological Attacks	< 1	Minor-Average
	Winter Storms	1-3	Minor-Extreme
	Earthquakes	< 1	Minor
Missouri	Hurricanes	< 1	-
	Floods	3-6	Minor
	Epidemics/Biological Attacks	< 1	-
	Major Organized Crime	< 1	-
	Hazardous Material Leaks	1-3	Average
	Winter Storms	5-25	Average-Extreme
	Earthquakes	< 1	Minor
Kansas	Floods	1-3	Minor-Average
	Epidemics/Biological Attacks	< 1	-
	Winter Storms	8-12	Minor-Extreme
	Tornados	-	-
Nebraska	Floods	4-6	Average
	Epidemics/Biological Attacks	< 1	Minor
	Hazardous Material Leaks	4-6	Average
	Winter Storms	> 6	Average

The responses in the historical data section show that the roles which the DOTs were expected to preform included:

- First responders
- Traffic control/detours
- Logistics
- Ensure the availability fuel and supplies(such as drinking water)
- Clean-up
- Coordinate with multiple agencies
- Stabilizing and re-establishing the highway infrastructure

These represent many of the same responsibilities which TxDOT is expected to contribute during disaster situations. It was found that only one of the respondents (Oregon) deviated from the emergency response procedure during the example emergencies described. Oregon was asked by the manager of the responsible agency to transport supplies to cities.

Though this was not a responsibility which the DOT had expected, they were somewhat prepared for it and will be expecting to provide this assistance in the future.

It was found that many of the state DOTs use human experience/intuition to decide when to replace/repair equipment. It was found that Pennsylvania uses a "Fleet Model" as their internal fleet management tool. It is seen however that many of the DOTs are leaning toward rental/leasing agreements rather that purchasing for equipment which is used less often (i.e., emergency situations).

Some of the respondents described that they would be changing their methods of fleet maintenance/reacquisition spending, while at the same time providing the highest level of fleet robustness. Oregon described that in March of 2013 they will be implementing a "new fleet information management system." Pennsylvania has an ongoing study to come up with a program to optimize the fleet replace/repair decision. Finally, Kansas is going through a complete review of their methods currently.

The survey identifies if/how other state DOTs manage their fleet with respect to disaster preparedness and how inadequate funding is addressed by other DOTs. Pennsylvania describes that they focus on the primary fleet first and do not consider secondary allocations until this need is met. This goes both for unavailability of funds and how Pennsylvania manages fleet with respect to disaster preparedness. This sentiment is shared by many of the respondents. However, Oregon was found to have fleet set aside and ready to rent or reallocate specifically for emergency situations. However, this fleet pool will be reduced in the following years because of budget shortfalls which have precedent on secondary fleet such as emergency vehicles.

The use of cost benefit analyses was also addressed, and the Pennsylvania respondent stated, "CBAs are one of our standard asset management tools. Although disaster response is recognized, the fact that the unit is needed for DR isn't the primary driver for ownership. The unit must have value to our overall programs." This further emphasizes the focus on core fleet requirements rather than emergency or secondary fleet needs. The Nebraska respondent stated that they must simply stay under the budget and they do not have a cost benefit analysis plan in place. These two views are echoed between the other respondents.

6.3.5 Discussion

The results gathered from Oregon and Pennsylvania may be the most relevant to TxDOT. This is because Oregon and Pennsylvania have a history of successfully responding to multiple disasters. Although the Pennsylvania and Oregon DOTs do not respond to the same types of disasters as TxDOT; their approach can give TxDOT inspiration and ideas about what to implement in its disaster response plans. The other DOT's plans can also provide TxDOT with valuable material.

6.4 Summary

In Chapter 6, the research team comprehensively reviewed and synthesized state of the practice of current fleet management procedures, and described how other state DOTs and major metropolitan governments' provision their fleets to handle multiple disasters. The methodology was used to construct a survey that determined how other state DOTs allocate resources to handle multiple simultaneous disasters. After distributing the survey via email to the various DOTs and waiting for responses; the research team compiled the available results into a user-friendly format for TxDOT. These results show how five other state DOTs handle fleet management with respect to disaster preparedness. Though the respondents do not encounter the same types of disasters as Texas, the data is useful in showing Texas possible provisions to prepare for multiple disaster scenarios.

Chapter 7. Data Analysis of Fleet Usage for TxDOT during Multiple Emergency Events

7.1 Introduction

As mentioned in previous chapters, Texas is a state that faces many potential disaster situations. Frequent natural disasters in the state include hurricanes and wildfires, as well as other forms of severe weather. In addition to these scenarios, Texas has to face the possibility of manmade disasters fluctuating from nuclear meltdowns to terrorist attacks. In light of these concerns, TxDOT is focusing on maintaining a robust fleet to meet its requirements to support DPS and Texas DEM. TxDOT also wishes to provide as much assistance as possible to the residents of the state of Texas. However, the fact that TxDOT has a fleet valued at $500,000,000 with an annual turnover rate of $50,000,000 has motivated TxDOT to 'right size' its fleet. This ongoing right sizing effort will also help the equipment replacement decision making process, potentially saving the taxpayers of the state of Texas a significant amount of money per year. As future funding levels become more uncertain, the lack of available funds necessary for optimal vehicle replacement is very likely. Also, as the availability of funds decreases, TxDOT must determine how this limitation will affect equipment purchasing and its fleet robustness. A level of robustness is needed in order to respond to two simultaneous disasters. TxDOT must list its levels of commitment to DPS and DEM. The purpose of this task is to collect historical fleet usage data during several disaster/emergency events and also conduct preliminary data analysis of the collected data.

Based on the survey of fleet management practices during emergency situations conducted in Chapter 6 as well as the discussions during the research progress meeting held on August 16, 2012, the research team is instructed to mainly focus our research efforts on likely simultaneous disaster/emergency events scenarios that include Hurricane and Wildfire. The data analyses are conducted and related numerical results are presented in detail.

7.2 Data Collection

The project team has been communicating and working closely with the Project Director (PD) and GSD personnel in collecting historical fleet usage data during several disaster/emergency events. Thanks TxDOT's kind help, the research team has successfully obtained such data on Wednesday October 24th 2012. Data includes but is not limited to, SNOW07 (Major Snow Event in West Texas), Y6ELP1 (2006 Flood in El Paso County), Y1SBWL (Super Bowl Event in Dallas Texas), Y9H001 (Hurricane Ike), and Y2R001 (Bastrop Complex Wildfire). Upon obtaining such data, the research team then performed data processing and conducted data analyses, which included but not limited to, historical activities by district, by season, by classcode, by equipment units, by event type, etc. Several advanced descriptive statistical analysis techniques are used to help extract useful information from the data. The findings are hereby summarized and presented through this section.

7.3 Data Analysis

Upon processing and analyzing the data, the frequency of four different events happened in the past is presented in the tables 7.1 and 7.2. These four events are Bastrop Fire Events, El Paso Flood Events, Hurricane Ike Events, and Super Bowl Events. From the analysis, maximum daily frequency of each equipment type by class code associated with the total mileage for the four different events that are identified. The total mileage is simply the aggregate sum of mileage of specific class code equipment unit associated with maximum daily frequency. For example, the maximum daily frequency of equipment units with classcode-1010 is 4, and the total mileage of these four equipment units is 22. And this maximum frequency occurred on specific date is 09-10-2011.

The summary of data on the four events is as presented in the Table 7.1.

Table 7.1 Summary of Data Analysis

Event (Year)	Total No. of Usage Events	Distinct No. of Class codes
Bastrop Fires (2011)	447	28
El Paso Floods (2006 & 2007)	652	28
Hurricane Ike (2008)	258	30
Super Bowl (2011)	2675	33

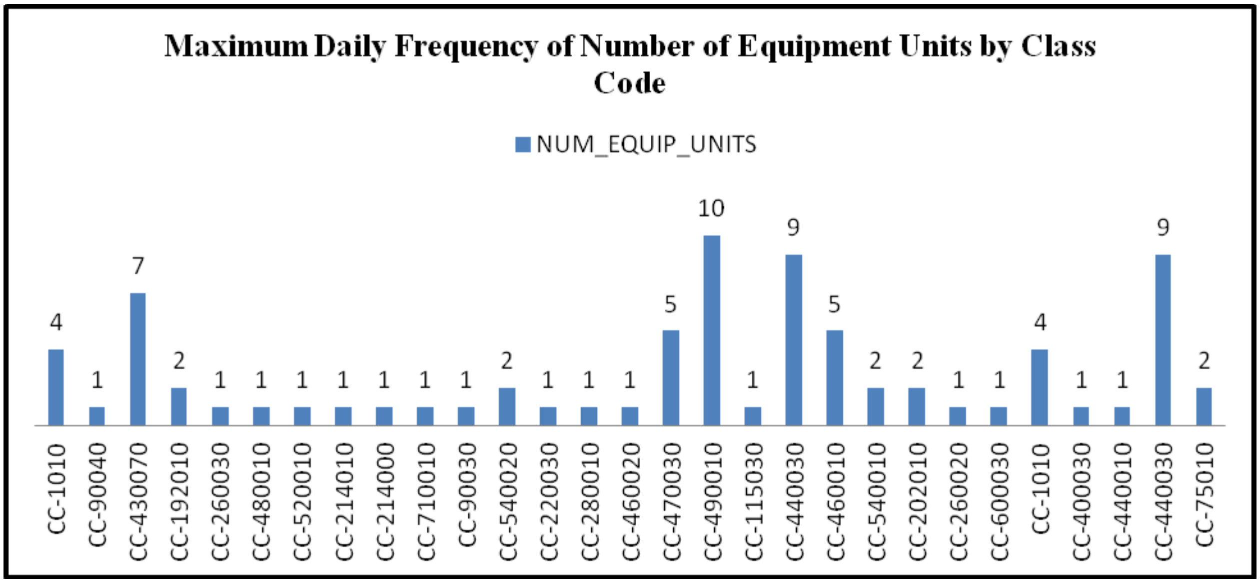
The following tables and figures present the maximum daily frequency of equipment units by classcode and the corresponding sum of mileage for specific date each event. The classcode description is also shown in the tables.

Table 7.2 Maximum Daily Frequency and Sum of Miles, Bastrop Fires Event (2011)

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2011	9	10	1010	AERIAL PERSONNEL DEVICE TRUCK MOUNTED UP TO 29' INC TRUCK	22	4
2011	9	10	90040	GRADER MOTOR CLASS IV 150 H.P. AND GREATER	5	1
2011	9	12	430070	TRUCK EXTENDED CAB 1/2 TON 6000 TO 6799 GVWR	534	7
2011	9	13	192010	SPRAYER HERBICIDE/INSECTICIDE TRUCK MOUNTED (INC. TRUCK)	5	2
2011	9	13	260030	TRAILER EQUIPMENT GOOSENECK	6	1
2011	9	13	480010	TRUCK PLATFORM PLATFORM DUMP STAKE 8600 TO 14 999 GVWR	14	1
2011	9	13	520010	TRUCK ALL BODY STYLES EXCEPT CONV. DUMP 21000 TO 25400 GVWR	30	1
2011	9	15	214010	TANK WATER TRUCK MOUNTED INCLUDES TRUCK	9	1
2011	9	19	214000	TANK WATER TRUCK MOUNTED INCLUDES TRUCK	89	1
2011	9	19	710010	VEHICLE ALL TERRAIN	6	1
2011	9	19	90030	GRADER MOTOR CLASS III 135 TO 149 H.P.	5	1
2011	9	27	540020	TRUCK DUMP TANDEM REAR AXLE 43000 GVWR AND GREATER (10 YARD)	295	2
2011	9	5	220030	TRACTOR CRAWLER TYPE (W/ OR W/O DOZER) 130 TO 179 H.P.	9	1
2011	9	5	280010	TRAILER TRANSPORT PLATFORM	2	1
2011	9	5	460020	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR OTHER BODY STYLES	202	1
2011	9	5	470030	TRUCK LIGHT DUTY CREW CAB 8600 TO 14 999 GVWR OTHER BODY STYLES	847	5
2011	9	5	490010	TRUCK LIGHT/MEDIUM 14 500 TO 18 999 GVWR	453	10
2011	9	6	115030	LOADER PNEUMATIC TIRED 2 CUBIC YARD	9	1
2011	9	6	440030	TRUCK EXTENDED CAB 3/4 TON 6800 TO 9000 GVWR	533	9

Table 7.2 Maximum Daily Frequency and Sum of Miles, Bastrop Fires Event (2011) ***(Continued)***

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2011	9	6	460010	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR PICKUP BODY	276	5
2011	9	6	540010	TRUCK DUMP SINGLE REAR AXLE 29000 TO 42900 GVWR (6 YARD)	113	2
2011	9	7	202010	SWEEPER ROAD SELF PROPELLED	3	2
2011	9	8	260020	TRAILER EQUIPMENT TILT BED OR UTILITY 24 000# CAP. AND GREATER	2	1
2011	9	8	600030	TRUCK TRACTOR TANDEM REAR AXLE ALL GCWR	89	1
2011	9	9	1010	AERIAL PERSONNEL DEVICE TRUCK MOUNTED UP TO 29' INC TRUCK	22	4
2011	9	9	400030	TRUCK 2-WD UTILITY VEHICLE 3961 TO 5000 GVWR	99	1
2011	9	9	440010	TRUCK LIGHT DUTY PICKUP 6200 TO 7999 LB. GVWR	139	1
2011	9	9	440030	TRUCK EXTENDED CAB 3/4 TON 6800 TO 9000 GVWR	533	9
2011	9	9	75010	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS I	4	2



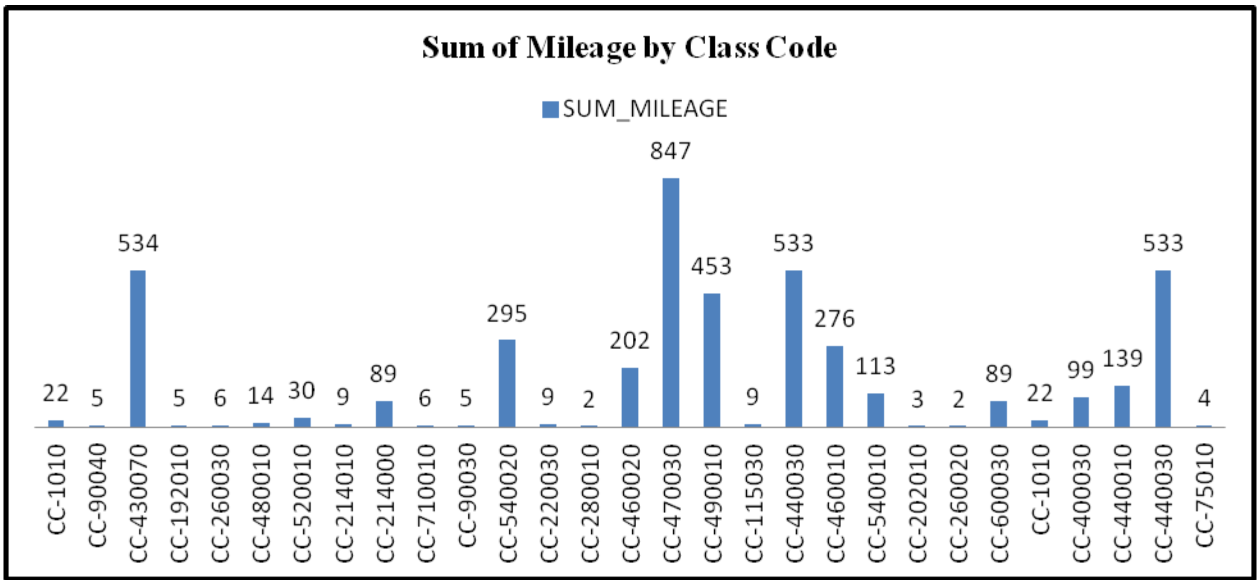


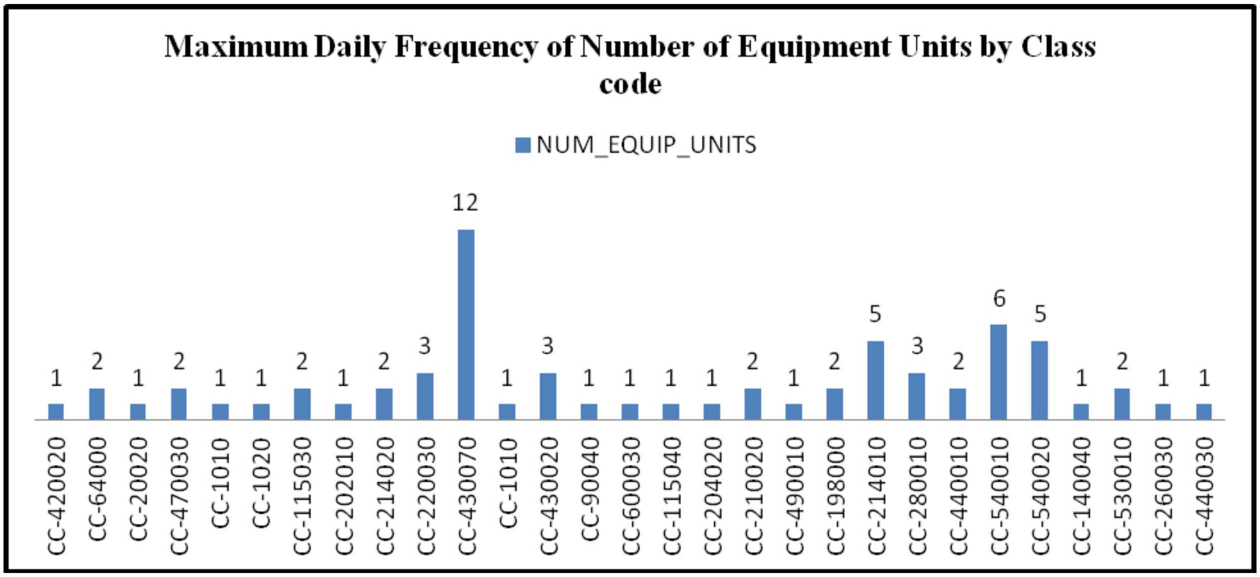
Figure 7.1 Maximum Daily Frequency and Sum of Miles, Bastrop Fires Event (2011)

Table 7.3 Maximum Daily Frequency and Sum of Miles, El Paso Floods Event (2006 & 2007)

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2006	10	16	420020	TRUCK CARGO OR WINDOW VAN FULL-SIZE 6200 LB GVWR AND GREATER	102	1
2006	10	16	64000	DYNAMIC DEFLECTION SYSTEM TRAILER MOUNTED	141	2
2006	12	19	20020	AUTOMOBILES SEDAN 100 THRU 112.9 IN. WHEELBASE	226	1
2006	8	22	470030	TRUCK LIGHT DUTY CREW CAB 8600 TO 14 999 GVWR OTHER BODY STYLES	105	2
2006	8	24	1010	AERIAL PERSONNEL DEVICE TRUCK MOUNTED UP TO 29' INC TRUCK	2	1
2006	8	25	1020	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 30 TO 39' INC TRUCK	2	1
2006	8	25	115030	LOADER PNEUMATIC TIRED 2 CUBIC YARD	15	2
2006	8	25	202010	SWEEPER ROAD SELF PROPELLED	10	1
2006	8	25	214020	TANK WATER TRAILER MOUNTED	22	2
2006	8	25	220030	TRACTOR CRAWLER TYPE (W/ OR W/O DOZER) 130 TO 179 H.P.	21	3
2006	8	25	430070	TRUCK EXTENDED CAB 1/2 TON 6000 TO 6799 GVWR	980	12
2006	8	29	1010	AERIAL PERSONNEL DEVICE TRUCK MOUNTED UP TO 29' INC TRUCK	2	1
2006	9	1	430020	TRUCK LIGHT DUTY PICKUP 4600 TO 6199 LB GVWR	460	3
2006	9	1	90040	GRADER MOTOR CLASS IV 150 H.P. AND GREATER	5	1
2006	9	12	600030	TRUCK TRACTOR TANDEM REAR AXLE ALL GCWR	71	1
2006	9	13	115040	LOADER PNEUMATIC TIRED 2 1/2 AND 3 CUBIC YARD	4	1

Table 7.3 Maximum Daily Frequency and Sum of Miles, El Paso Floods Event (2006 & 2007) *(Continued)*

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2006	9	13	204020	SWEEPER STREET TRUCK MOUNTED	3	1
2006	9	14	210020	TANK FUEL TRAILER MOUNTED	9	2
2006	9	22	490010	TRUCK LIGHT/MEDIUM 14 500 TO 18 999 GVWR	166	1
2006	9	5	198000	STORM & DRAIN PIPE CLEANING UNIT TRUCK MOUNTED	6	2
2006	9	5	214010	TANK WATER TRUCK MOUNTED INCLUDES TRUCK	23	5
2006	9	5	280010	TRAILER TRANSPORT PLATFORM	17	3
2006	9	5	440010	TRUCK LIGHT DUTY PICKUP 6200 TO 7999 LB. GVWR	444	2
2006	9	5	540010	TRUCK DUMP SINGLE REAR AXLE 29000 TO 42900 GVWR (6 YARD)	2153	6
2006	9	5	540020	TRUCK DUMP TANDEM REAR AXLE 43000 GVWR AND GREATER (10 YARD)	2181	5
2006	9	7	140040	PAINT STRIPE MACHINE TWO COLOR MULTI-LINE TRUCK MOUNTED	6	1
2006	9	7	530010	TRUCK ALL BODY STYLES EXCEPT CONV. DUMP/WRECKER 25500-28900 GVWR	145	2
2006	9	8	260030	TRAILER EQUIPMENT GOOSENECK	9	1
2007	3	2	440030	TRUCK EXTENDED CAB 3/4 TON 6800 TO 9000 GVWR	62	1



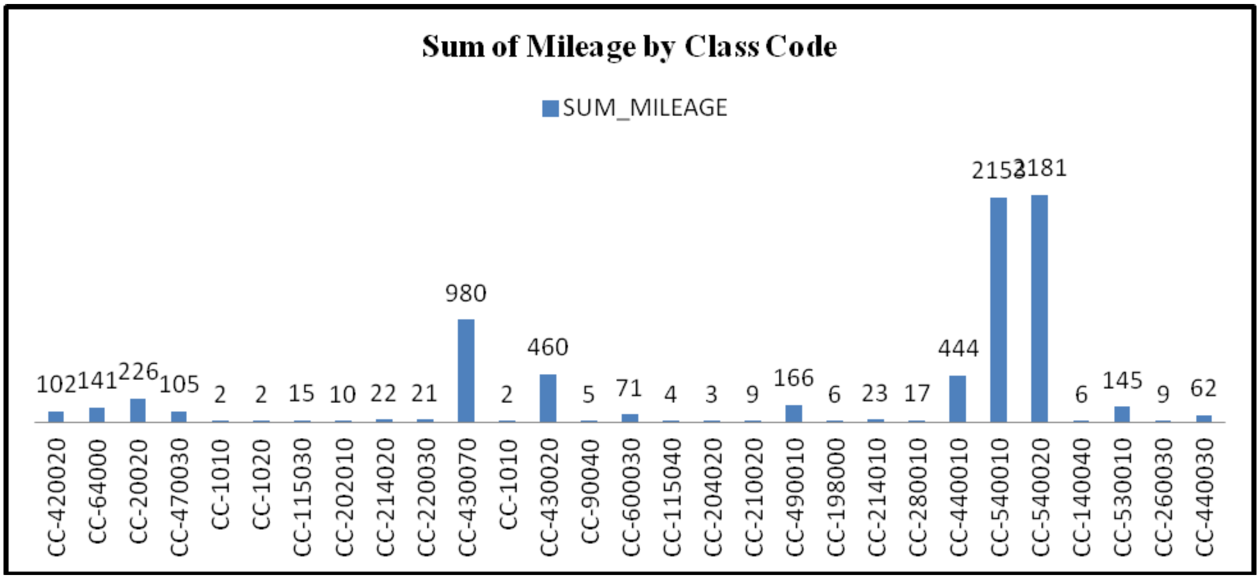


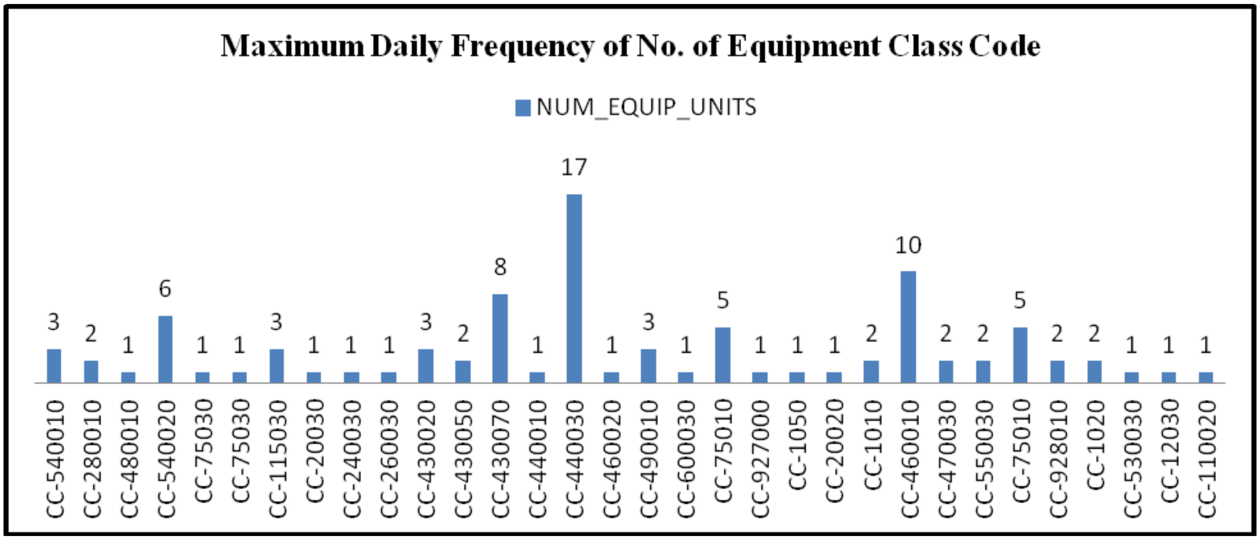
Figure 7.2 Maximum Daily Frequency and Sum of Miles, El Paso Floods Event (2006/2007)

Table 7.4 Maximum Daily Frequency and Sum of Miles, Hurricane Ike Event (2008)

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2008	11	10	540010	TRUCK DUMP SINGLE REAR AXLE 29000 TO 42900 GVWR (6 YARD)	410	3
2008	11	25	280010	TRAILER TRANSPORT PLATFORM	10	2
2008	11	25	480010	TRUCK PLATFORM PLATFORM DUMP STAKE 8600 TO 14 999 GVWR	103	1
2008	11	25	540020	TRUCK DUMP TANDEM REAR AXLE 43000 GVWR AND GREATER (10 YARD)	922	6
2008	12	1	75030	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS III	5	1
2008	12	3	75030	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS III	5	1
2008	9	13	115030	LOADER PNEUMATIC TIRED 2 CUBIC YARD	4	3
2008	9	13	20030	AUTOMOBILES SEDAN 113 IN. WHEELBASE AND GREATER	65	1
2008	9	13	240030	TRACTOR PNEUMATIC TIRED W/ LOADER AND BACKHOE 60 H.P. AND ABOVE	2	1
2008	9	13	260030	TRAILER EQUIPMENT GOOSENECK	4	1
2008	9	13	430020	TRUCK LIGHT DUTY PICKUP 4600 TO 6199 LB GVWR	157	3
2008	9	13	430050	TRUCK EXTENDED CAB COMPACT 4245 TO 5034 GVWR	50	2
2008	9	13	430070	TRUCK EXTENDED CAB 1/2 TON 6000 TO 6799 GVWR	191	8
2008	9	13	440010	TRUCK LIGHT DUTY PICKUP 6200 TO 7999 LB. GVWR	15	1
2008	9	13	440030	TRUCK EXTENDED CAB 3/4 TON 6800 TO 9000 GVWR	1165	17
2008	9	13	460020	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR OTHER BODY STYLES	49	1
2008	9	13	490010	TRUCK LIGHT/MEDIUM 14 500 TO 18 999 GVWR	357	3
2008	9	13	600030	TRUCK TRACTOR TANDEM REAR AXLE ALL GCWR	10	1

Table 7.4 Maximum Daily Frequency and Sum of Miles, Hurricane Ike Event (2008) ***(Continued)***

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2008	9	13	75010	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS I	7	5
2008	9	13	927000	TRAILER EQUIPMENT 1-1/2 THRU 3 TON	3	1
2008	9	14	1050	AERIAL PERSONNEL DEVICE TRUCK MOUNTED MILEAGE	12	1
2008	9	14	20020	AUTOMOBILES SEDAN 100 THRU 112.9 IN. WHEELBASE	195	1
2008	9	15	1010	AERIAL PERSONNEL DEVICE TRUCK MOUNTED UP TO 29' INC TRUCK	3	2
2008	9	15	460010	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR PICKUP BODY	341	10
2008	9	15	470030	TRUCK LIGHT DUTY CREW CAB 8600 TO 14 999 GVWR OTHER BODY STYLES	95	2
2008	9	15	550030	TRUCK ALL STYLES EXCEPT DUMP SINGLE REAR AXLE 29000-38900 GVWR HRLY	50	2
2008	9	15	75010	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS I	7	5
2008	9	15	928010	TRAFFIC ALERTING & CHANNELING DEVICE ARROW TRLR MTD SOLAR POWERED	10	2
2008	9	16	1020	AERIAL PERSONNEL DEVICE TRUCK MOUNTED 30 TO 39' INC TRUCK	3	2
2008	9	16	530030	TRUCK EJECTION TYPE MATERIAL BODY 25500 TO 38900 GVWR	24	1
2008	9	17	12030	ASPHALT MAINTENANCE UNIT TRUCK MOUNTED	3	1
2008	9	18	110020	LOADER CRAWLER 2 CU. YD. CAPACITY AND GREATER	2	1



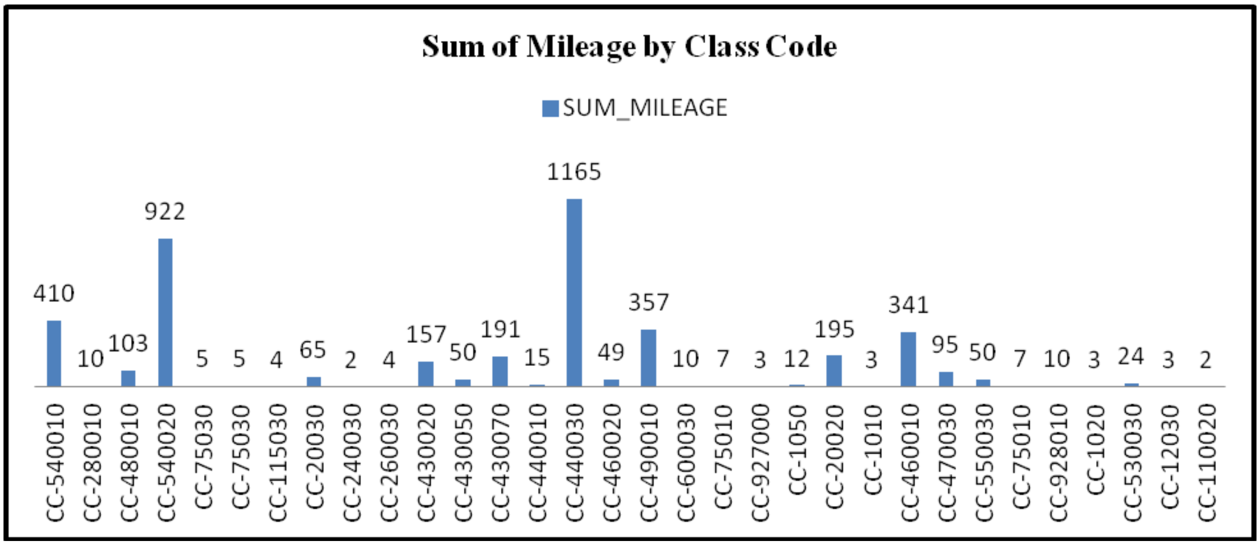


Figure 7.3 Maximum Daily Frequency and Sum of Miles, Hurricane Ike Event (2008)

Table 7.5 Maximum Daily Frequency and Sum of Miles, Super Bowl Event (2011)

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2011	1	31	260030	TRAILER EQUIPMENT GOOSENECK	94	7
2011	1	31	550010	TRUCK ALL STYLES EXCEPT DUMP SINGLE REAR AXLE 29000-38900 GVWR	381	1
2011	2	1	240030	TRACTOR PNEUMATIC TIRED W/ LOADER AND BACKHOE 60 H.P. AND ABOVE	9	2
2011	2	1	480010	TRUCK PLATFORM PLATFORM DUMP STAKE 8600 TO 14 999 GVWR	201	7
2011	2	1	85020	FORKLIFT ENGINE DRIVEN 4000 LB. AND OVER OPERATING CAP.	16	2
2011	2	2	420020	TRUCK CARGO OR WINDOW VAN FULL-SIZE 6200 LB GVWR AND GREATER	35	2
2011	2	2	430020	TRUCK LIGHT DUTY PICKUP 4600 TO 6199 LB GVWR	3672	32
2011	2	2	600030	TRUCK TRACTOR TANDEM REAR AXLE ALL GCWR	908	6
2011	2	3	110020	LOADER CRAWLER 2 CU. YD. CAPACITY AND GREATER	34	2
2011	2	3	115000	LOADER PNEUMATIC TIRED SKID STEER	17	2
2011	2	3	115030	LOADER PNEUMATIC TIRED 2 CUBIC YARD	38	5
2011	2	3	115040	LOADER PNEUMATIC TIRED 2 1/2 AND 3 CUBIC YARD	68	6
2011	2	3	192010	SPRAYER HERBICIDE/INSECTICIDE TRUCK MOUNTED (INC. TRUCK)	39	9
2011	2	3	400030	TRUCK 2-WD UTILITY VEHICLE 3961 TO 5000 GVWR	466	4
2011	2	3	440030	TRUCK EXTENDED CAB 3/4 TON 6800 TO 9000 GVWR	3660	37
2011	2	3	470030	TRUCK LIGHT DUTY CREW CAB 8600 TO 14 999 GVWR OTHER BODY STYLES	823	13
2011	2	3	75030	EXCAVATOR TELESCOPING BOOM CARRIER MOUNTED CLASS III	24	3
2011	2	4	190010	SNOW PLOW HIGH SPEED EXPRESS WAY 10 FT.	250	52
2011	2	4	190020	SNOW PLOW STRAIGHT MOLDBOARD 10 FT.	563	112

Table 7.5 Maximum Daily Frequency and Sum of Miles, Super Bowl Event (2011) *(Continued)*

EVENT_ YEAR	EVENT_ MONTH	EVENT_ DAY	CLASS_ CODE	CLASS_CODE_DESC	SUM_ MILEAGE	NUM_EQUIP_ UNITS
2011	2	4	204040	SWEEPER STREET TRUCK MOUNTED REGENERATIVE AIR 6 CU.YD. AND GREATER	15	1
2011	2	4	430070	TRUCK EXTENDED CAB 1/2 TON 6000 TO 6799 GVWR	2179	27
2011	2	4	440010	TRUCK LIGHT DUTY PICKUP 6200 TO 7999 LB. GVWR	630	5
2011	2	4	460010	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR PICKUP BODY	740	9
2011	2	4	490010	TRUCK LIGHT/MEDIUM 14 500 TO 18 999 GVWR	580	6
2011	2	4	540020	TRUCK DUMP TANDEM REAR AXLE 43000 GVWR AND GREATER (10 YARD)	16096	221
2011	2	4	90020	GRADER MOTOR CLASS II 110 TO 134 H.P.	11	1
2011	2	4	90030	GRADER MOTOR CLASS III 135 TO 149 H.P.	49	10
2011	2	5	280010	TRAILER TRANSPORT PLATFORM	24	3
2011	2	5	420010	TRUCK CARGO OR WINDOW VAN MINI UP TO 6200 LB GVWR	136	3
2011	2	5	530010	TRUCK ALL BODY STYLES EXCEPT CONV. DUMP/WRECKER 25500-28900 GVWR	688	1
2011	2	5	540010	TRUCK DUMP SINGLE REAR AXLE 29000 TO 42900 GVWR (6 YARD)	6356	104
2011	2	6	460020	TRUCK LIGHT DUTY 8600 TO 14 999 GVWR OTHER BODY STYLES	301	3
2011	2	7	600020	TRUCK TRACTOR SINGLE REAR AXLE 60000 GCWR AND GREATER	240	1

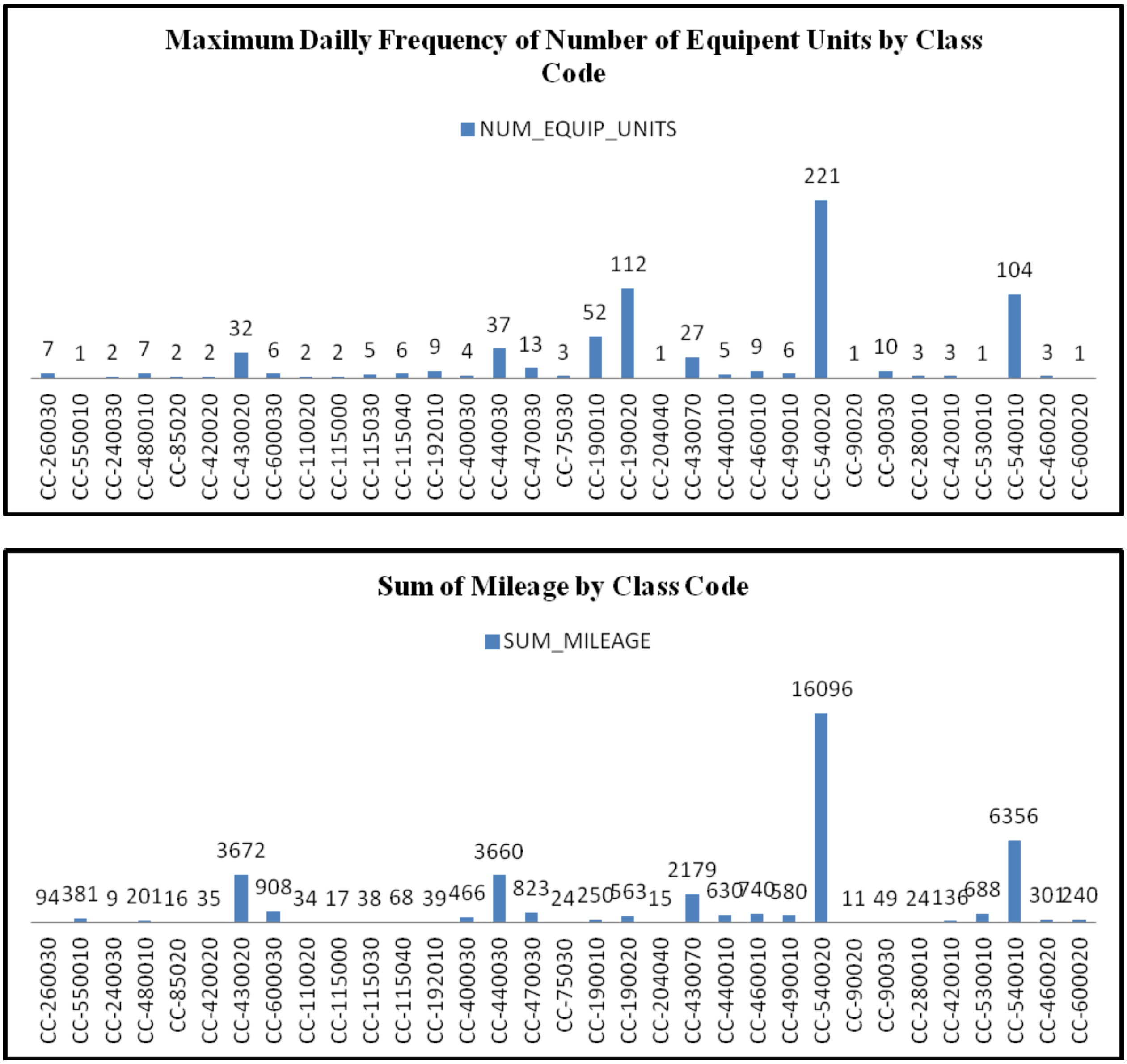


Figure 7.4 Maximum Daily Frequency and Sum of Miles, Super Bowl Event (2011)

7.4 Identifying the Two Most Likely Simultaneous Emergency Events

TxDOT equipment utilizations for the four actual disaster scenarios obtained from TxDOT historical records are Hurricane (Coastal Plains area), Flood (El Paso area), Forest Fire (Austin area), and Super Bowl Ice Storm (Dallas area). Out of these four possible disaster scenarios, a hurricane is more frequent, and as such has been considered one of the two possible disaster events. The remaining three disaster events are more of a seasonal nature occurring at specific time periods of a year. Based on these considerations, a hurricane along with any one of the other three events (flood, fire, and super bowl) were identified as two of the most likely simultaneous disaster/emergency scenarios in Texas.

Based on historical equipment utilization data on disaster/emergency scenario management, equipment requirement for two simultaneous disaster scenarios has been estimated. Maximum number of units utilized for each vehicle class code for the three disaster events (flood, forest fire, and Super Bowl) has been identified and added with the number of units utilized for the most likely disaster event—a hurricane. This sum represents the "worst case" from historical data. Total 59 vehicle classcodes have been identified for two simultaneous disaster/emergency scenarios. Figure 7.5 shows the top ten equipment class codes required for two simultaneous disaster/emergency scenarios. Table 7.6 lists all the 59 equipment class codes and their requirement for two simultaneous emergency events. In Table 7.7, locational distribution of all the 59 equipment class codes among the four TxDOT zones is summarized. Figure 7.6 demonstrates graphically the distribution of the top most required equipment for emergency response among the TxDOT zones.

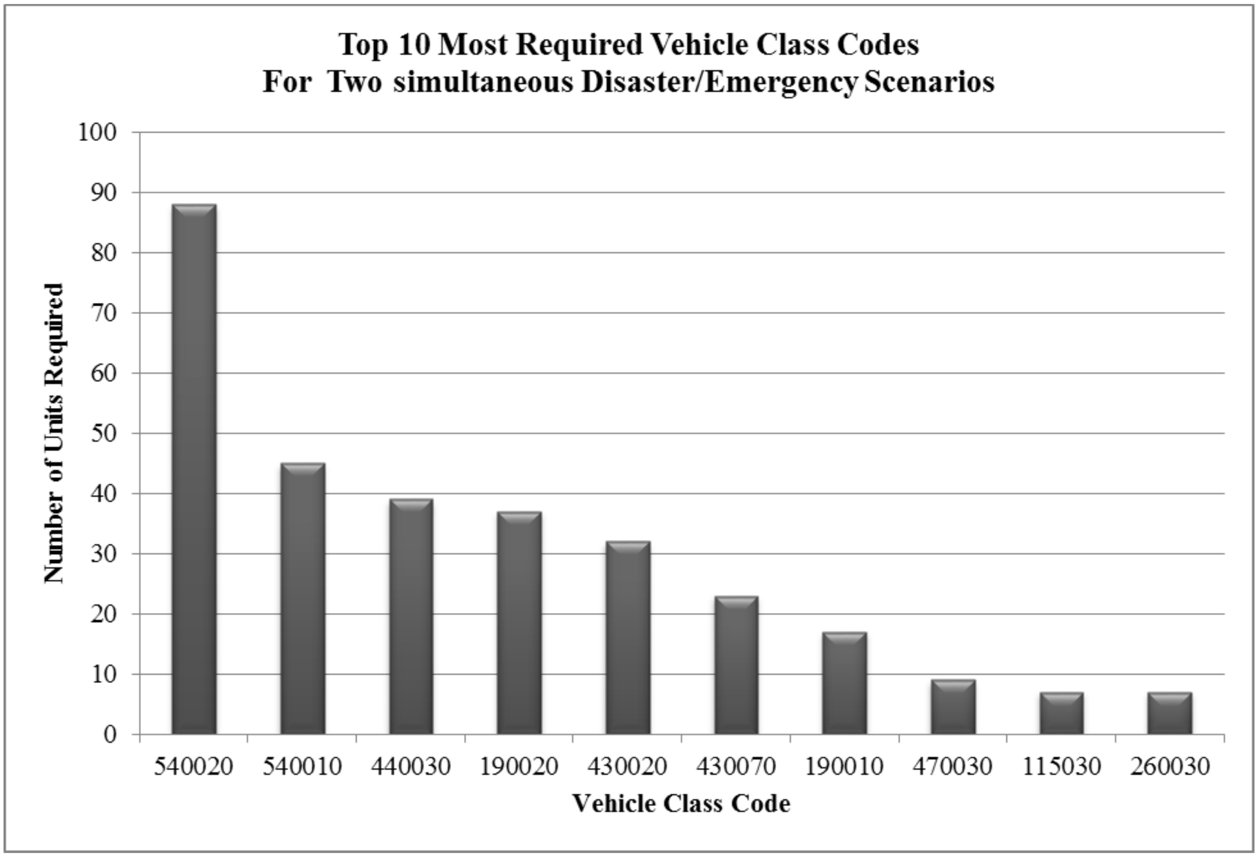


Figure 7.5 List of Top 10 Vehicle Class Codes Required for Addressing Two Simultaneous Disaster/Emergency Scenarios in Texas

Table 7.6 Maximum Equipment Requirement Based on Historical Equipment Commitment for Disaster/Emergency Scenarios in Texas

Serial No.	Vehicle Class	Hurricane	Flood	Fire	Super bowl	Maximum of flood, fire & Super Bowl	Maximum requirement for hurricane and another simultaneous event
1	540020	6	5	2	82	82	88
2	540010	3	6	2	42	42	45
3	440030	12	1	6	27	27	39
4	190020	0	0	0	37	37	37
5	430020	3	3	0	29	29	32
6	430070	5	8	6	18	18	23
7	190010	0	0	0	17	17	17
8	470030	1	1	5	8	8	9
9	115030	3	2	1	4	4	7
10	260030	1	1	1	6	6	7
11	460010	2	0	2	5	5	7
12	490010	1	1	4	5	5	6
13	600030	1	1	1	5	5	6
14	1010	2	1	3	0	3	5
15	280010	2	3	1	2	3	5
16	75010	3	0	1	0	1	4
17	90030	0	0	1	4	4	4
18	192010	0	0	2	4	4	4
19	460020	1	0	1	3	3	4
20	1020	2	1	0	0	1	3
21	110020	1	0	0	2	2	3
22	115040	0	1	0	3	3	3
23	214010	0	3	1	0	3	3
24	240030	1	0	0	2	2	3
25	400030	0	0	1	3	3	3
26	440010	1	2	1	2	2	3
27	20020	1	1	0	0	1	2
28	75030	1	0	0	1	1	2
29	85020	0	0	0	2	2	2
30	214020	0	2	0	0	2	2
31	220030	0	2	1	0	2	2
32	420010	0	0	0	2	2	2

Table 7.6 Maximum Equipment Requirement Based on Historical Equipment Commitment for Disaster/Emergency Scenarios in Texas *(Continued)*

Serial No.	Vehicle Class	Hurricane	Flood	Fire	Super bowl	Maximum of flood, fire & Super Bowl	Maximum requirement for hurricane and another simultaneous event
33	430050	2	0	0	0	0	2
34	480010	1	0	1	1	1	2
35	530010	0	2	0	1	2	2
36	1050	1	0	0	0	0	1
37	12030	1	0	0	0	0	1
38	20030	1	0	0	0	0	1
39	64000	0	1	0	0	1	1
40	90020	0	0	0	1	1	1
41	90040	0	1	1	0	1	1
42	115000	0	0	0	1	1	1
43	140040	0	1	0	0	1	1
44	198000	0	1	0	0	1	1
45	202010	0	1	1	0	1	1
46	204020	0	1	0	0	1	1
47	204040	0	0	0	1	1	1
48	210020	0	1	0	0	1	1
49	214000	0	0	1	0	1	1
50	260020	0	0	1	0	1	1
51	420020	0	1	0	1	1	1
52	520010	0	0	1	0	1	1
53	530030	1	0	0	0	0	1
54	550010	0	0	0	1	1	1
55	550030	1	0	0	0	0	1
56	600020	0	0	0	1	1	1
57	710010	0	0	1	0	1	1
58	927000	1	0	0	0	0	1
59	928010	1	0	0	0	0	1

Table 7.7 Distribution of Required Equipment for Two Simultaneous Disaster/Emergency Scenarios among the Four TxDOT Zones based on 2011 Data

		Number of units in each region in 2011					Percentage of Units in each region in 2011				
Serial No.	Vehicle Class	E	N	S	W	Total	E	N	S	W	Total
1	540020	104	247	191	227	769	13.5	32.1	24.8	29.5	99.9
2	540010	93	228	158	302	781	11.9	29.2	20.2	38.7	100
3	440030	11	228	140	130	509	2.2	44.8	27.5	25.5	100
4	190020	0	20	0	150	170	0	11.8	0	88.2	100
5	430020	371	225	239	66	901	41.2	25	26.5	7.3	100
6	430070	163	668	386	394	1611	10.1	41.5	24	24.5	100.1
7	190010	0	14	0	182	196	0	7.1	0	92.9	100
8	470030	26	50	35	54	165	15.8	30.3	21.2	32.7	100
9	115030	27	65	56	88	236	11.4	27.5	23.7	37.3	99.9
10	260030	21	41	31	23	116	18.1	35.3	26.7	19.8	99.9
11	460010	43	103	44	25	215	20	47.9	20.5	11.6	100
12	490010	77	72	121	100	370	20.8	19.5	32.7	27	100
13	600030	14	24	23	29	90	15.6	26.7	25.6	32.2	100.1
14	1010	18	55	33	24	130	13.8	42.3	25.4	18.5	100
15	280010	46	75	75	115	311	14.8	24.1	24.1	37	100
16	75010	18	37	14	3	72	25	51.4	19.4	4.2	100
17	90030	18	45	36	23	122	14.8	36.9	29.5	18.9	100.1
18	192010	47	57	64	50	218	21.6	26.1	29.4	22.9	100
19	460020	29	70	26	28	153	19	45.8	17	18.3	100.1
20	1020	13	64	27	58	162	8	39.5	16.7	35.8	100
21	110020	5	24	2	6	37	13.5	64.9	5.4	16.2	100
22	115040	5	23	26	42	96	5.2	24	27.1	43.8	100.1
23	214010	3	14	14	9	40	7.5	35	35	22.5	100
24	240030	18	34	40	44	136	13.2	25	29.4	32.4	100
25	400030	69	37	48	19	173	39.9	21.4	27.7	11	100
26	440010	74	63	32	21	190	38.9	33.2	16.8	11.1	100
27	20020	9	34	29	19	91	9.9	37.4	31.9	20.9	100.1
28	75030	7	8	3	3	21	33.3	38.1	14.3	14.3	100
29	85020	19	70	53	62	204	9.3	34.3	26	30.4	100
30	214020	3	2	7	9	21	14.3	9.5	33.3	42.9	100
31	220030	1	10	2	9	22	4.5	45.5	9.1	40.9	100
32	420010	2	16	5	3	26	7.7	61.5	19.2	11.5	99.9
33	430050	18	52	4	4	78	23.1	66.7	5.1	5.1	100
34	480010	4	24	23	13	64	6.3	37.5	35.9	20.3	100

Table 7.7 Distribution of Required Equipment for Two Simultaneous Disaster/ Emergency Scenarios among the Four TxDOT Zones Based on 2011 Data *(Continued)*

		Number of units in each region in 2011					Percentage of Units in each region in 2011				
Serial No.	**Vehicle Class**	**E**	**N**	**S**	**W**	**Total**	**E**	**N**	**S**	**W**	**Total**
35	530010	3	15	9	5	32	9.4	46.9	28.1	15.6	100
36	1050	14	2	6	14	36	38.9	5.6	16.7	38.9	100.1
37	12030	24	53	58	65	200	12	26.5	29	32.5	100
38	20030	4	23	20	12	59	6.8	39	33.9	20.3	100
39	64000	0	0	0	0	0	0	0	0	0	0
40	90020	24	71	43	26	164	14.6	43.3	26.2	15.9	100
41	90040	9	15	8	92	124	7.3	12.1	6.5	74.2	100.1
42	115000	24	63	19	78	184	13	34.2	10.3	42.4	99.9
43	140040	0	1	2	4	7	0	14.3	28.6	57.1	100
44	198000	0	1	0	1	2	0	50	0	50	100
45	202010	16	74	63	101	254	6.3	29.1	24.8	39.8	100
46	204020	4	15	5	10	34	11.8	44.1	14.7	29.4	100
47	204040	3	13	9	4	29	10.3	44.8	31	13.8	99.9
48	210020	21	6	9	5	41	51.2	14.6	22	12.2	100
49	214000	1	3	6	0	10	10	30	60	0	100
50	260020	1	11	7	8	27	3.7	40.7	25.9	29.6	99.9
51	420020	10	17	7	9	43	23.3	39.5	16.3	20.9	100
52	520010	1	10	7	4	22	4.5	45.5	31.8	18.2	100
53	530030	5	19	2	0	26	19.2	73.1	7.7	0	100
54	550010	9	12	4	3	28	32.1	42.9	14.3	10.7	100
55	550030	0	2	10	0	12	0	16.7	83.3	0	100
56	600020	0	13	7	1	21	0	61.9	33.3	4.8	100
57	710010	9	9	11	35	64	14.1	14.1	17.2	54.7	100.1
58	927000	5	40	20	59	124	4	32.3	16.1	47.6	100
59	928010	34	95	72	50	251	13.5	37.8	28.7	19.9	99.9

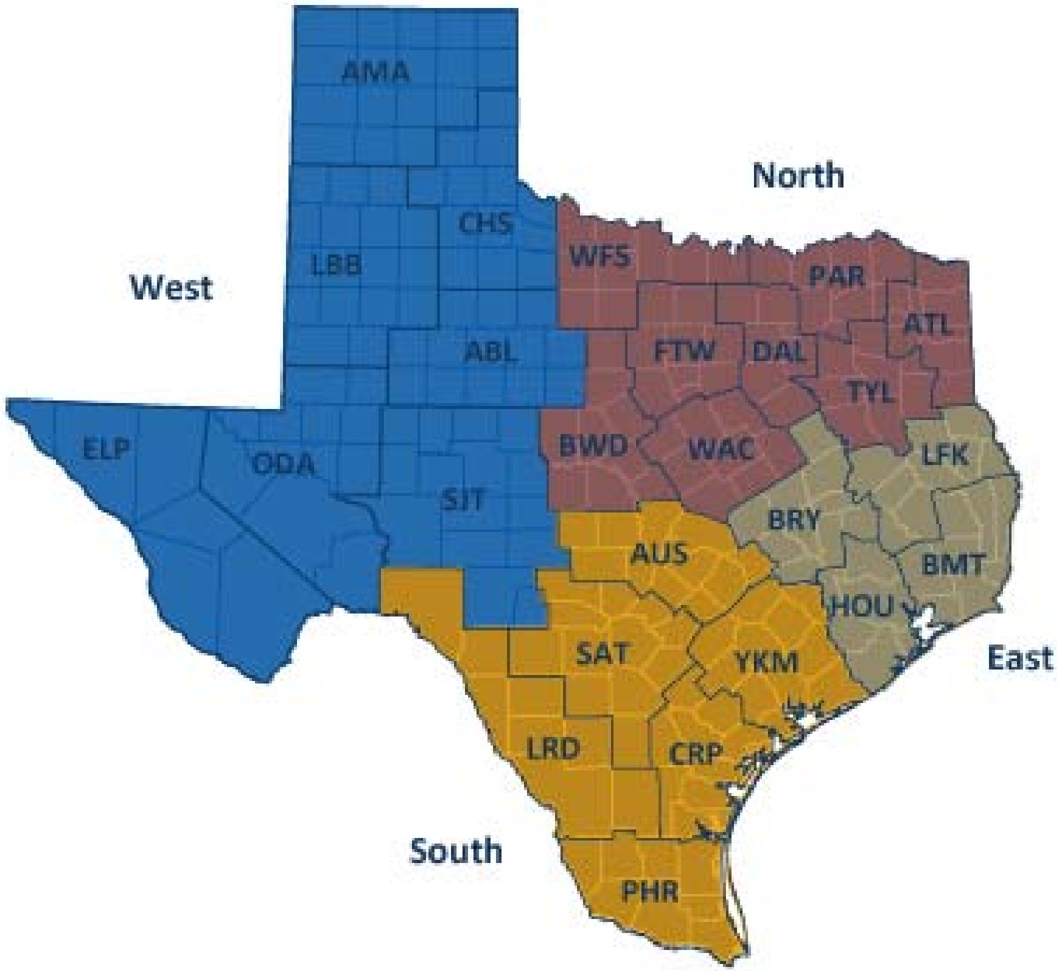


Figure 7.6 Zones and Zonal Distribution of Vehicle Class Code 540020 based on 2011 Data

7.5 Summary

The project team collected historical fleet usage data during several disaster/emergency events, performed data processing, and conducted data analyses, which included historical activities by district, by season, by classcode, by equipment units, by event type, etc. Several advanced descriptive statistical analysis techniques were used to help extract useful information in the data processing stage.

The maximum daily frequency of each equipment class code associated with the total mileage was identified for all four events (including Bastrop Fire Events, El Paso Flood Events, Hurricane Ike Events, and Super Bowl Events). In addition, the two most likely simultaneous disaster/emergency scenarios were identified from the analysis. Out of the four possible disaster scenarios, a hurricane is more frequent and therefore, it has been considered one of the two most possible disaster events. The remaining three disaster events are considered to be more of a seasonal nature occurring at specific time periods of the year. Therefore, hurricane along with any one of the other three events (flood, fire, and super bowl) was identified as two most likely simultaneous disaster/emergency scenarios in Texas.

Chapter 8. Summary and Conclusions

8.1 Introduction

The TxDOT vehicle fleet is a fundamental part of the departmental infrastructure, enabling many activities essential to accomplishing the daily departmental operations. Maintenance of a robust vehicle fleet is essential but costly. On one hand, reductions in fleet costs are potentially beneficial to the department as a whole and thereby beneficial to the taxpayers of the State of Texas. On the other hand, not being able to respond adequately under disaster/emergency conditions is unacceptable and therefore maintaining a fleet robust enough to capably respond in a multi-event contingency is also critical.

The primary objective of this report is to address the equipment replacement/retention decision making problems associated with uncertain funding levels. In order to address the problem, several advanced mathematical optimization algorithms as well as robust statistical estimating and forecasting models have been developed and implemented as part of the new TERM2 equipment replacement optimization methodology and in TxDOT's rightsizing efforts. The result of this project will provide users the ability to use these advanced analytical tools to assess a variety of costs (purchase cost and down time cost) and impacts of being unable to execute optimal equipment keep/replace decisions under different scenarios as well as other future uncertainties.

8.2 Summary and Conclusions

This report addressed several issues involved with TxDOT's recent equipment replacement optimization software (TERM2) produced through project 0-6412 "equipment Replacement Optimization'' (ERO) that can optimize the equipment retain/replace decision process. As discussed before, TERM2 ERO is a dynamic programming (DP) based optimization solution methodology and consists of the following three main components: 1) A SAS Macro based Data Cleaner and Analyzer, which undertakes the tasks of data reading, cleaning, and analyzing, as well as cost estimation and 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 users, displays the final results of the optimization, and coordinates the optimization engine and SAS macro data cleaner and analyzer.

In order to accomplish this project, the research team has undertaken several tasks. First, a comprehensive review of the state of the art and state of the practice on the use and development of advanced optimization techniques in the current TERM2 equipment replacement optimization as results of the TxDOT project 0-6412, as well as the use and development of advanced optimization techniques to solving the optimal fleet vehicle allocation and facility location problems, particularly under disaster/emergency event scenarios, was conducted. Then, several issues related to the original strategy implemented to estimate and forecast future equipment purchase costs for project 0-6412 were identified. Several strategies have been developed and tested and the best method has been identified and implemented in the new TERM2 software to investigate future uncertain purchase costs due to technology changes and to model the future uncertain purchase costs. The impact of future uncertain equipment purchase costs on equipment replacement decision making is also investigated through the conducted sensitivity analyses. Also, optimization and evaluation framework were also developed in the new TERM2 software to investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced (i.e., determine the increase in cost when delaying replacing equipment). In addition, the down time costs, operations and maintenance (O&M) costs, and mileage forecasting methods in the previous ERO software were also reviewed. Several issues were identified and modification strategies have been developed and implemented in the new TERM2 software to improve their forecasts. Furthermore, Texas' emergency management strategy and support concept and list levels of commitment to the DEM and DPS, particularly from the fleet management perspective, were comprehensively reviewed. A comprehensive online survey of how other state DOTs and major metropolitan governments provide their fleets to handle multiple disasters currently nationwide were also conducted. The survey results were analyzed the state of the practice were comprehensively reviewed and documented. Finally, TxDOT's historical fleet usage data during several disaster/emergency events were collected and analyzed. Based on the analysis, the two most likely simultaneous events in Texas were identified.

In the original strategy implemented to forecast future equipment purchase costs for project 0-6412, SAS macro source codes were developed for linear model, polynomial model, logarithm model, exponential model, power model and the best-fit model will be identified and selected. However, it was revealed through investigation, the software was selecting best-fit models that could yield decreasing and in some cases negative purchase costs for future years. In order to prevent the software from utilizing decreasing purchase costs, an alternative strategy is developed and implemented in this project. The alternative strategies included implementation of a factor based on the inflation rate in place of a statistical model, use of manufacturer suggested retail price in place of historical purchase cost, addition of commodity price index variables as predictors, utilization of moving averages for purchase cost, examination of other equations with high quality of fit and creation of simple linear models.

Among the various models, a linear model was determined to be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of application in an algorithm, and its provision of a relatively good fit overall for any data trends. However, the linear model should pass the three threshold tests (sample size greater than 6 entries, R-square value greater than 0.60, and slope greater than 0). If any one of these thresholds is not met, then a default option would be applied. The default option is multiplying the current year's purchase cost by one-half of the inflation rate to establish the value of the subsequent year which accounts for an annual increase in purchase cost beyond inflation. The algorithm to conduct the above processes is developed by using SAS macros code and implemented in the new software.

The level of success as a result of the implementation of the algorithm was thoroughly evaluated. The algorithm was tested for 75 class codes and all of them showed an increasing forecasted purchase cost. Sensitivity analysis of the inflation rate was also conducted to investigate the impact of future uncertain equipment purchase cost on equipment replacement decision making for both Cost Current Trend and Cost Equal Mileage approaches. For Cost Current Trend, inflation rate affects the optimal replacement age generally by increasing the optimal replacement equipment age with higher inflation rates or the equipment age remains constant. On the other hand, for Cost Equal Mileage, inflation rate affects the optimal replacement equipment age of the heavyweight equipment by generally decreasing as the inflation rate increases.

Optimization and evaluation framework were also developed to investigate how to estimate costs to the department of NOT replacing equipment when it should be replaced (i.e., determine the increase in cost when delaying replacing equipment) as a result of implementation and integration of the second round Knapsack Programming optimization framework with the DP optimization methodology in the new TERM2 software. Therefore, the ERO under annual budget constraint can now be successfully considered. The optimal equipment replacement decision now involves two rounds of optimization (DDP/SDP + Knapsack Programming, another linear integer programming model). The main objective of this Knapsack programming is to maximize the benefits produced (i.e., minimize the total cost increases due to delay for equipment replacement) in order to embody a mixture of both TxDOT's short-term and long-term interests. In particular, a DP-based optimization engine, which consists of the DDP and SDP based solution approaches, both Bellman's and Wagner's formulations, have been developed and implemented for solving the ERO problem.

In this project, a practical rate for down time hours for each individual classcode is established. The original strategy for estimating down time was to use one universal rate (a baseline rate of $25 per hour) for all of the classcodes in the TxDOT TERM database. However, this estimate was limited, as different vehicle types are likely to incur a different cost due to being out of service. However, it was decided that this rate would not adequately assess the difference in cost associated with down time for different types of vehicles or equipment and varying nature of their assigned tasks. The rental rate was chosen as an adequate assessment of down time cost based on the established precedence for its use and due to the limited information available relative to down time in the TxDOT database. The information provided identifies only the number of annual, down time hours incurred for each vehicle. To accomplish the task of assigning a down time cost, the rental rate for each classcode was determined using information obtained from various sources in the equipment and vehicle rental industry. The base rental rates for each classcode were then multiplied by the risk factor to establish the final down time rate used by the program.

In addition to establishing a practical rate for down time hours for each individual classcode, the overall O&M costs were evaluated. The original strategy for forecasting the O&M costs developed for project 0-6412 depended on the use of SAS, as initiated by the graphical user interface (GUI), to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast equipment O&M costs for two different strategies: cost current trend and cost equal mileage. Through an in-depth evaluation of the software results, it was discovered that the O&M cost forecasts for a number of the classcodes was unduly influencing the keep/replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that, in some cases, yielded negative O&M costs for future years.

Various strategies, as a result of different issues identified through the study of this project, were considered to improve the O&M cost forecasting method. One of the issues identified included high, early O&M costs across many of the classcodes. An appropriate strategy was developed and approved for modifying the first two years of cost data prior to being utilized for generating statistical models. Another issue found was the forecast of negative O&M costs based on the statistical models. It was determined that replacing these negative forecasts with minimum, annual O&M cost values, calculated from the historical TERM data, would be appropriate for resolving this problem. It was also determined that establishing a minimum O&M cost rates would be necessary for populating missing entries (due to zero O&M costs or utilization recorded for specific vehicles) for the cost equal mileage option. In addition, as part of the statistical model generating process, models generated will be evaluated against a minimum

R-squared value for goodness-of-fit, along with a second outlier removal process, were necessary for improving the accuracy of forecasted results. Lastly, it was found that minimal sample sizes within the data, including that for purchase cost information, would need to be accounted for in the establishment of forecasted costs as this has a substantial impact on the ability of the optimization engine to provide cost comparisons and appropriate keep versus replace decisions.

Discussing TxDOT's levels of commitment from the perspective of fleet management, as well as to ascertain how uncertain equipment costs will affect future replacement decision making is one of the tasks in this project. Texas, as of now, has disaster plans in place for hurricanes, nuclear fallout/radiological source contamination, hazardous material leaks, health and medical disasters and terrorist attack scenarios. However, these plans are vague, as each individual disaster can, and most likely would, be different from every other occurrence. The research team conducted a survey, comprehensively reviewed and synthesized the state of the practice of current fleet management procedures, and described how other state DOTs and major metropolitan governments' provide their fleets to handle multiple disasters and how inadequate funding is addressed by other DOTs. Though the respondents do not encounter the same types of disasters as Texas, the data is useful in showing Texas possible provisions to prepare for multiple disaster scenarios. Particularly, the results gathered from Oregon and Pennsylvania may be the most relevant to TxDOT. This is because Oregon and Pennsylvania have a history of successfully responding to multiple disasters.

In addition, the project team collected TxDOT's historical fleet usage data during several disaster/emergency events, performed data processing, and conducted data analyses, which included historical activities by district, by season, by classcode, by equipment units, by event type, etc. Data such as SNOW07 (Major Snow Event in West Texas), Y6ELP1 (2006 Flood in El Paso County), Y1SBWL (Super Bowl Event in Dallas Texas), Y9H001 (Hurricane Ike), and Y2R001 (Bastrop Complex Wildfire) were included. Several advanced descriptive statistical analysis techniques were used to help extract useful information such as event date, class code type, sum of mileage and number of equipment used for all four events (i.e., Bastrop Fire Events, El Paso Flood Events, Hurricane Ike Events, and Super Bowl Events). From the analysis, maximum daily frequencies of each equipment class code associated with the total mileage for all four different events were identified.

Moreover, the two most likely simultaneous disaster events in Texas were determined through this research. As data obtained from TXDOT's equipment utilization indicated, out of these four possible disaster scenarios, hurricane is more frequent and as such has been considered as one of the two possible disaster events while the remaining three disaster events are more of a seasonal nature occurring at specific time periods of a year. Accordingly, hurricane along with any one of the other three events (flood, fire, and super bowl) was identified as of two most likely simultaneous disaster/emergency scenarios in Texas. The maximum number of units utilized for each vehicle class code for the three disaster events (flood, forest fire, and Super Bowl) has been identified and added with the number of units utilized for the most likely disaster event: hurricane.

In conclusion, the main purpose of this project was to develop more robust statistical models to improve forecasting future uncertain purchase costs, down time costs, O&M costs, and annual usage; and advanced optimization methodology to facilitate the equipment replacement decision process under budget uncertainty. The newly developed TERM2 ERO software as results of this project is very general and can be used to make optimal keep/replace decisions for each/all districts, for both brand-new and used vehicles, both with and without annual budget considerations, based on the equipment classcode, age, mileage, salvage value, and replacement cost either obtained externally or calculated internally by using the developed SAS macro codes. Numerical results indicate that a significant amount of cost savings can be estimated by using the developed TERM2 ERO software.

8.3 Future Research Directions

The new TERM2 software addressed various issues identified as results of investigating the previous ERO software results. Different statistical modeling strategies and optimization frameworks were implemented to improve the quality of the new TERM2 results. Major improvements include provision of better forecasting method for uncertain equipment purchase cost, enabling the software to determine costs to the department due to delay in replacing equipment, establishment of practical rates for down time hours for each and every individual classcode, and improvements to the O&M costs and mileage forecasting. As a result, a more robust and reliable TERM2 ERO software was developed and a significant amount of cost savings have been estimated by using the new TREM2.

As more TERM data accumulates and becomes more readily available in future years, future equipment purchase costs and O&M costs estimating and forecasting results will become more reliable and robust, which will certainly help continue to improve the solutions produced by using TERM2 software and significant cost savings can be thus expected.

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Appendix A: Robust Statistical Estimating and Forecasting Models Used to Investigate the Future Uncertain Purchase Costs Due to Technology Changes and the Down Time Costs Coupled with TxDOT's Current Rightsizing Efforts

0-6693-P1

Chapter A.1. Forecasting Models to Investigate Future Uncertain Purchase Costs due to Technology Changes

The purpose of this task was to investigate future uncertain purchase costs due to technology changes and recommend feasible ways to model the future purchase costs given the historical data. The original approach was to incorporate models developed as part of project 0-6412 into the software; however, issues were discovered with these forecasting methods and modifications to the strategy were considered and, ultimately, implemented.

Based on the TxDOT TERM data, the research team developed five different types of models (including Linear/Polynomial/Logarithm/Exponential/Power models) in TERM2 as results of project 0-6412 to investigate the future uncertain purchase costs due to technology changes using model year as the independent variable. Although the models seemed to perform well from a technical perspective, some purchase cost forecasts did not yield intuitive results. For some classcodes, even the best forecasting model derived from historical purchase cost data may yield negative forecasts for purchase cost due to the economic downturn that occurred in the latter years of the TERM data sets. The research team explored the use of both linear and nonlinear statistical modeling techniques, as well as strategies involving fixed increases to the forecasted purchase costs based on the inflation rate, to develop the best possible forecasts due to technology changes and other uncertainties. After a feasible (and potentially most desirable) way to model the future uncertain purchase costs was identified, it was incorporated into the TERM2 equipment replacement optimization software.

In addition to developing models for estimating future uncertain purchase costs, the research team also explored the potential of emerging vehicle fuel technologies and their possible impacts on future purchase costs. Traditionally, the transportation industry relies heavily on conventional petroleum based fuels (diesel and gasoline). About two-thirds of U.S. petroleum demand is in the transportation sector and almost half of U.S. petroleum is imported. This high dependency on foreign petroleum supplies puts the United States at risk for trade deficits, supply disruption, and price changes. Development of new and alternative vehicle fuel technologies has the potential to reduce U.S. dependency on petroleum imports and provide future energy security.

A.1.1 Introduction

As mentioned above, the original strategy for forecasting the purchase cost was developed for project 0-6412. This involved development of multiple statistical models to forecast equipment purchase costs. Upon implementation of the above strategy, some forecasted purchase costs were found to be much lower than expected, and in some extreme cases, negative. This prompted the research team to do a full review of the purchase cost forecasts for each class code. It was discovered that the issue of decreasing forecasted purchase costs was fairly extensive due in large part to recorded lower purchase cost values near the end of the recorded period. This finding led to development of a strategy intended to prevent the software from utilizing decreasing purchase cost forecasts. The obstacles discovered using the original approach, as well as the development of an alternate strategy and its subsequent implementation into the software package, are further described in the following sections. Also, emerging alternative vehicle fuel technologies and their possible effects on future uncertain purchase costs are presented in the later parts.

A.1.2 Original Strategy and Obstacles Identified

The strategy for forecasting the purchase cost developed for project 0-6412 depended on the use of SAS, as initiated by the graphical user interface (GUI), to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast equipment purchase cost versus model year. In particular, the SAS macro source codes were developed for the following five different types of models: 1) Linear Model; 2) Polynomial Model; 3) Logarithm Model; 4) Exponential Model; and 5) Power Model.

The SAS macro could run through all of the linear and nonlinear models and automatically identify the best-fit model, per the highest R-squared value, for forecasting the equipment purchase cost (using model year) for any chosen classcode. The objective was to use SAS to create and select the best-fit model for the data and incorporate that model for forecasting purchase costs into the optimization engine. For more information about the development of these models and the selection process, see Fan et al. (2011a, 2011b).

Through the evaluation of early versions of the software, it was discovered that purchase cost forecasts for a number of classcodes were unduly influencing the keep/replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that yielded decreasing, and in some cases negative, purchase costs for future years. The evaluation of the quality of the fit (R-squared value) for the model options led to the software choosing non-linear models for many of the equipment classcodes. Due to the distribution of data for some of these equipment types, this resulted in a curvilinear model with a negative slope generated over the years near the end of the recorded history of purchase costs, as illustrated in Figure A.1.1.

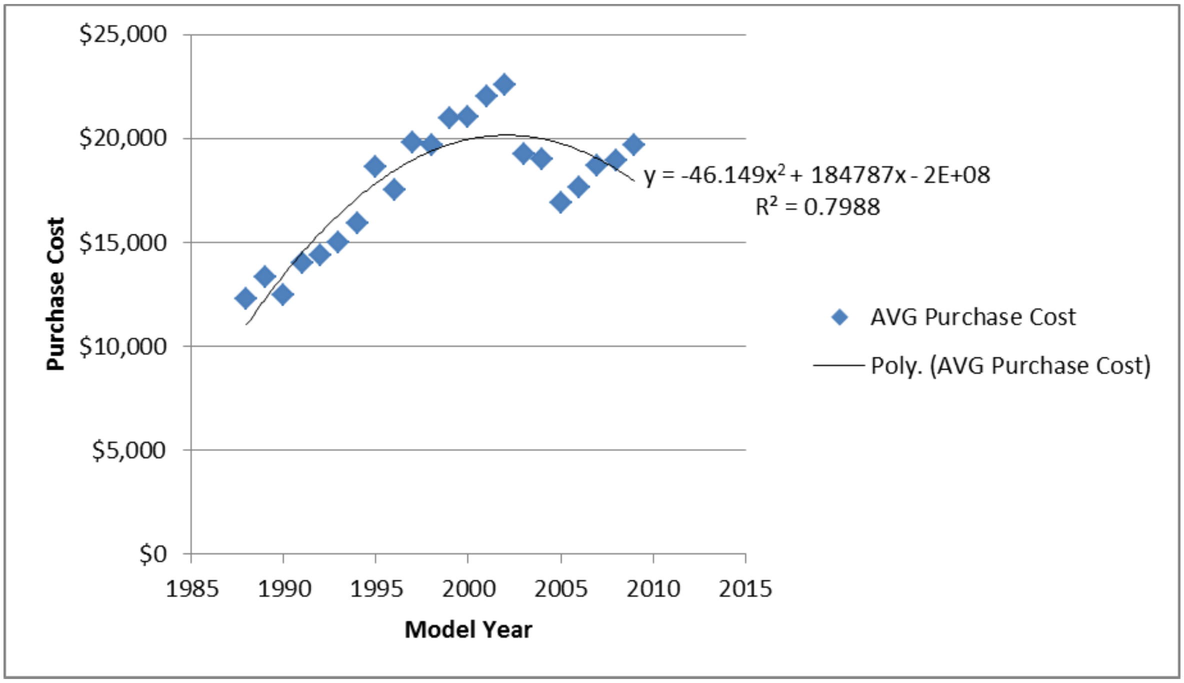


Figure A.1.1 Average Purchase Cost Versus Model Year With Vest-fit Model for Classcode 430070 (Light Duty Truck)

Note that Figure A.1.1 shows the nonlinear model yielding a good fit for the data (R-squared value of 0.7988); however, the slope of the model is negative at the end of the existing time period and would subsequently result in decreasing future year forecasted purchase costs. It was determined that this would have a detrimental impact on the ability of the optimization engine to appropriately generate recommendations for replacing equipment, as the long-term decreasing trend is counterintuitive. As such, several methods of troubleshooting the problem were identified and tested.

A.1.3 Development and Implementation of an Alternate Strategy

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

A.1.3.1 Testing Alternate Strategies

The use of a factor based on the inflation rate, in order to increase the forecasted purchase cost by a given percentage based on the last year of data available, was tested first. While this method solved the issue of a decreasing forecasted purchase cost, it did not take into account the historical purchase cost data beyond the last year recorded. It was determined that this would not be a universally effective method for forecasting purchase costs as it does not always effectively demonstrate the overall trend of the data. However, it was designated as an alternative if the other methods failed to yield better results. One of those options was including supplemental explanatory variables, in addition to model year, in the forecasting model.

The variables chosen for testing included MSRP, Consumer Price Index (CPI), and Producer Price Index (PPI). These values were readily attainable for including in the model; however, an evaluation of a multitude of variable combinations did not produce a robust solution. The MSRP was initially designated for replacing the purchase cost data in the model. It was anticipated that using the MSRP as a response variable with model year as the predictor would result in a more stable model. While the MSRP model was found to demonstrate a smoother trend, with a less pronounced tendency toward decreasing purchase prices than the historical purchase cost information, a negative slope still developed in the long-term forecast (20 years). Using MSRP in place of the actual purchase cost data yielded improved results, but it didn't solve the underlying issue; therefore, several alternatives utilizing consumer and producer price indices were evaluated.

The alternatives tested included adding the price indices to the models with either historical purchase cost or MSRP as the response variable. The overall CPI was tested, as well as the CPI for trucks, both trucks and automobiles, and new vehicles only (excluding used vehicle purchases). The PPI for automobiles, light trucks, and utility vehicles was also assessed. While inclusion of the price indices was shown to improve short-term forecasts of purchase price (approximately 5 years), it did not yield satisfactory results for longer-term forecasts. Forecasted prices were shown to far exceed expected trends for purchase costs over a 20-year horizon. Therefore, additional options were developed for investigation.

The option of using moving averages to dampen the effect of the negative trend for the purchase cost was also evaluated. The use of two-year, three-year, and four-year moving averages was attempted. It was determined that using a moving average resulted in a flattening of the purchase cost curve, but the model repeatedly failed to demonstrate the ability to forecast a purchase price that was not inhibited by a negative slope. Again, the fundamental problem remained. It was decided to further evaluate the additional models created by the statistical analysis software from the original data, other than the one chosen by the software as the best fit.

Although the other models did not demonstrate the best overall fit, they were investigated for their ability to project an increasing purchase cost in the future. It was discovered that many of the polynomial, logarithm, exponential, and power models developed by the statistical analysis software produced a good fit for the data; however, the vast majority resulted in projecting a decreasing purchase cost or otherwise counter-intuitive projection of purchase cost. In the end, it was determined that the simple linear model provided a reasonably good fit for the data while projecting an increasing purchase cost in the future. The linear model was therefore chosen as the best model for projecting the purchase cost for the light duty truck, classcode 430070.

Per the results for the light duty truck, a linear model was subsequently developed for all of the classcodes in the database. Overall, the data and subsequent models for 125 classcodes were evaluated. In some cases, troubleshooting was required to improve the fit of the models. This involved investigating the data for outliers or model year price information influenced by relatively few entries. In these cases, the data were cleaned to yield better results. The data for some similar classcodes were combined to improve the results for codes where relatively small, individual sample sizes were available for the model's development.

This process resulted in a series of models based on the existing data that could be used to forecast more dependable purchase cost trends. In addition, the simplified approach enables the more stable linear model to be efficiently updated given additional purchase cost data obtained in the future, without the risk of an extensive alteration to the model formula. While this process appeared to yield a relatively robust solution to the aforementioned problem of decreasing forecasted purchase costs, it involved the creation of appropriate linear models manually. Therefore, a variation of this strategy was devised for implementation that could be automatically duplicated by the software via an algorithm.

A.1.3.2 Developing a Software Algorithm

To determine whether an automated process could be implemented to create and evaluate linear models for forecasting purchase costs, a series of test runs were completed to develop an algorithm. These tests were carried out in Excel and involved the manual evaluation of 75 classcodes. Each classcode was evaluated by determining if a linear model, created from the historical TERM data, met thresholds for sample size, goodness of fit, and slope. The thresholds were established as follows: sample size greater than 6 entries (or years for which purchase cost data exists within the last 20), R-square value greater than 0.60, and slope of the linear model greater than 0. The intent was for a linear model that passes all three checks to be chosen to forecast the purchase cost in the software. It was determined that a linear model would be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of application in an algorithm, and its provision of a relatively good fit overall for any data trends. It was discovered for the non-inflation rate adjusted purchase cost data that a linear model captured the historical trends quite well. However, it should be noted that the inflation adjusted purchase cost was ultimately utilized for the forecasting strategy. Figure A.1.2, illustrates an example where this strategy would be utilized for forecasting purchase cost, i.e., the linear model created passes all three of the thresholds.

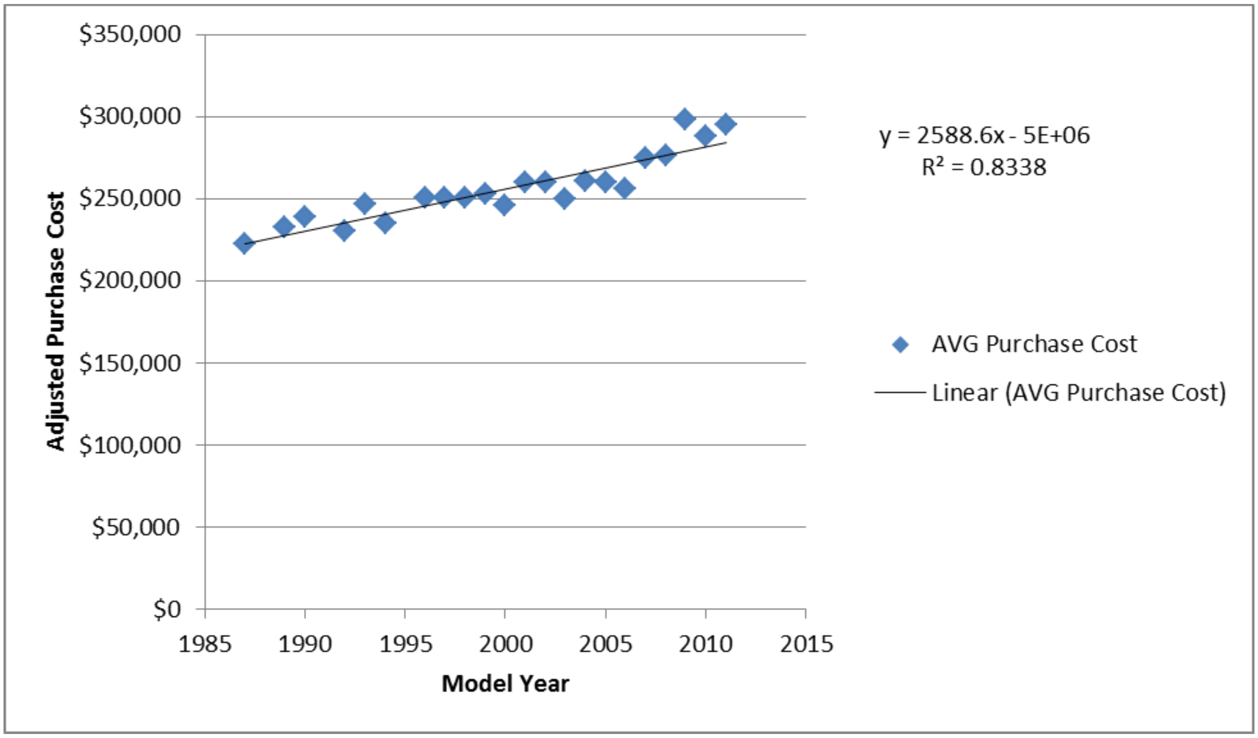


Figure A.1.2 Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 75010 (Excavator, Telescoping Boom, Carrier Mounted)

If any of the aforementioned thresholds are not met by the created model, then a default option is to be utilized. The purpose of this strategy is to provide a fail-safe to ensure that an increasing purchase cost is always forecasted. The default option for forecasting the purchase cost was chosen to be a formula where one-half of the inflation rate (inflation rate currently input as 3.2649%) is multiplied by the current year's purchase cost to establish the value for the subsequent year. Specifically, the purchase cost for each future year is based on the previous year's adjusted purchase cost multiplied by one plus one-half of the inflation rate (1.0163245). This strategy was chosen based on input from prior meetings with TxDOT personnel where it was suggested that the inflation rate be used as a multiplier in order to guarantee an increasing purchase cost is forecasted.

It should be noted that one-half of the inflation rate was chosen since the values input into the model for purchase cost have inflation built into them, i.e., the one-half inflation rate multiplier is to account for an annual increase in purchase cost beyond inflation. This results in a gradual increase in adjusted purchase cost that subtly accounts for uncertainties involved in predicting future changes. Furthermore, use of the inflation adjusted purchase cost data helped to ensure appropriate values for the forecasted purchase cost were input into the optimization engine, as well as to guarantee that no further adjustments would be made to the values *after* the forecasting process that might otherwise result in failing the threshold tests. Figure A.1.3 illustrates an example where the linear model created for the adjusted purchase cost failed the threshold test for goodness of fit and the inflation rate adjustment would be utilized as the forecasting method.

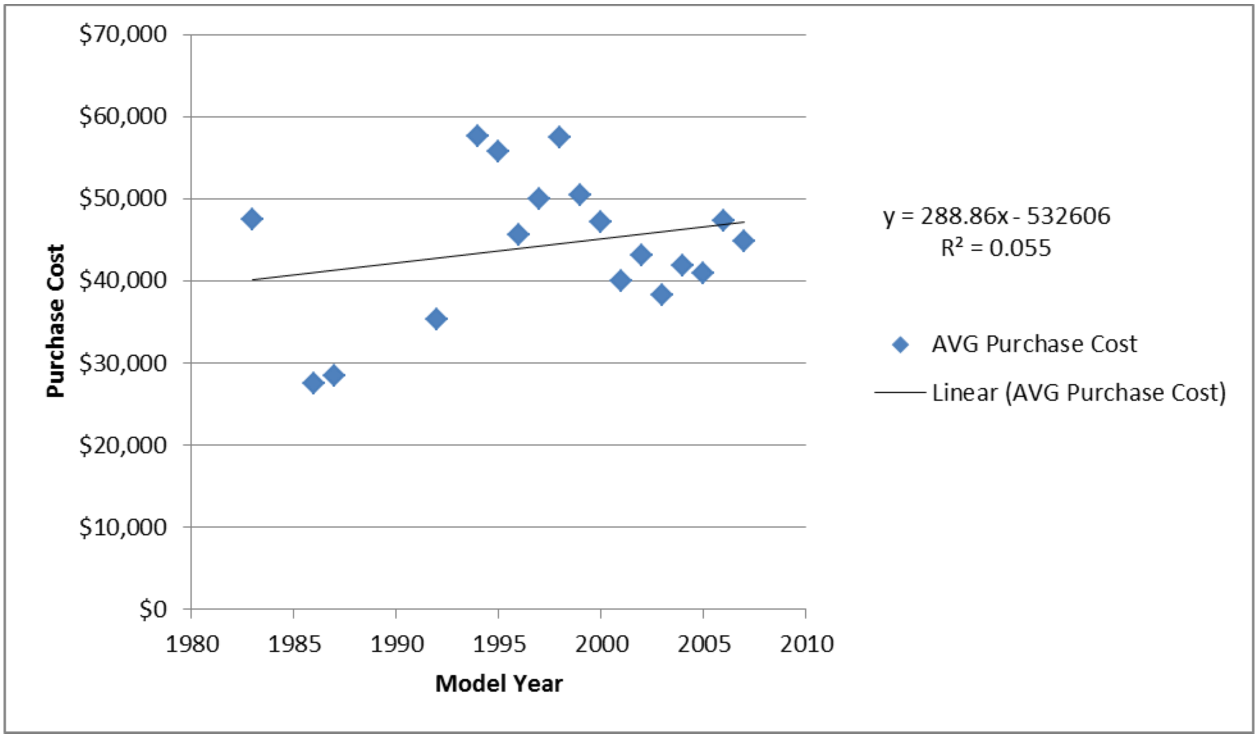


Figure A.1.3 Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 115000 (Loader, Pneumatic Tired, Skid Steer)

Before finalizing the algorithm for implementation into the software, a check was initiated to ensure the data sets used to create the linear models were thoroughly evaluated. In addition to the SAS macro based data cleaning process, another outlier removal procedure was implemented as part of the algorithm to eliminate major outliers from the data before the linear models are created by the software. To see more information about the SAS macro based data cleaning process involving the first outlier treatment, see Fan et al. (2011a). In the second round of the outlier removal process, upper and lower thresholds are created for a range of acceptable values. Those thresholds are calculated based on the lower and upper quartiles (Q_1 and Q_3) and the subsequent interquartile range ($IQR = Q_3 - Q_1$) as follows:

$$F_1 \text{ (lower threshold)} = Q_1 - [2 * 1.5 * (Q_3 - Q_1)]$$
$$F_3 \text{ (upper threshold)} = Q_3 + [2 * 1.5 * (Q_3 - Q_1)]$$

As such, adjusted purchase cost values falling outside the thresholds are eliminated from consideration for the creation of the linear models. With the outlier removal process and the three threshold tests determined, along with the primary and secondary (default) forecasting options established, details for the algorithm were finalized. The algorithm was now ready to move from the conceptual stage to implementation in the software.

A.1.3.3 Implementing the Algorithm

The implementation process for the aforementioned software algorithm, as developed using SAS macro codes, is provided in Figure A.1.4.

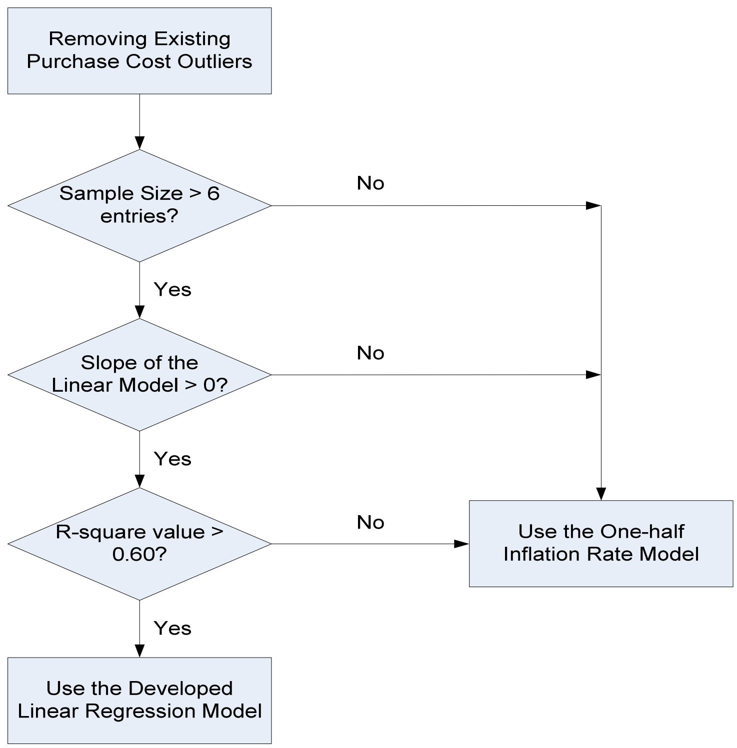


Figure A.1.4 Flow Chart of the Purchase Cost Forecasting Algorithm Software Implementation

As shown in Figure A.1.4, the algorithm first removes the remaining outliers for the purchase cost across all model years using the aforementioned IQR method. Then, it checks the following three conditions: whether or not the sample size (i.e., the data entries for average purchase cost) is greater than 6; whether or not the slope of the linear model is positive; and whether or not the R-squared value is great than 0.6. If any of these three condition checks fail, then the software will use the one-half inflation rate model to conduct the future purchase cost forecast. On the other hand, if all three condition checks pass, the software will use the developed linear regression model.

A.1.3.4 Reviewing the Results

In order to review the level of success achieved from applying the algorithm, the forecasted purchase costs for the classcodes were thoroughly evaluated. The same 75 classcodes identified for the manual testing were again selected for a detailed review of the software algorithm. All 75 classcodes were found to have an increasing forecasted purchase cost for the 20-year horizon. In fact, the algorithm resulted in increasing forecasted purchase costs for all of the classcodes, as intended. It was also discovered from the 75 classcodes selected, that using the inflation adjusted purchase cost had a major impact on the number of classcodes with linear models that passed all three-algorithm thresholds. Therefore, it was concluded that removing the effect of inflation from the purchase cost had a significant impact on the data's tendency to possess a measurable trend, both identified and utilized by the software.

Specifically, the results indicated that the software algorithm generally outputs a forecasted purchase cost based on the halved inflation rate due to the failure of the linear model to meet the goodness of fit threshold. As more TERM data becomes available in future years, this trend may change. The more comprehensive the purchase cost data sets, the more likely a linear model will provide an acceptable fit and be selected; thus, the forecasted purchase cost will be based on the historical data. In either case, the algorithm will continue to provide a robust solution for forecasting the purchase cost with increasing values, as well as encapsulating more intuitive trends.

Chapter A.2. U.S. Energy Scenario and Potential Future Directions

Alternative fuel technologies are attracting increasing attention as conventional fuel prices (gasoline and diesel) continue to increase. A myriad of factors contribute in this ascension, among which geographic distribution and potential reserves of crude oil are the two most significant determinants of world fuel price. The ever increasing need of crude oil by countries all over the world, whether developed, developing or under-developed, as a primary means to meet energy demand resulting from rapid industrialization and increased living standards is also contributing significantly in the rise of crude oil based fuel prices. Figure A.2.1 shows the average monthly retail fuel prices in the United States from 2000 to 2013. The price of petroleum fuels (gasoline and diesel fuel) acts as the primary driver of overall fuel prices. As petroleum prices rise, so does demand for alternative fuels, thereby pushing their prices upward as well. However, natural gas prices have been buffered from this driver, because its primary market is utilities, and due to recent increases in domestic natural gas production.

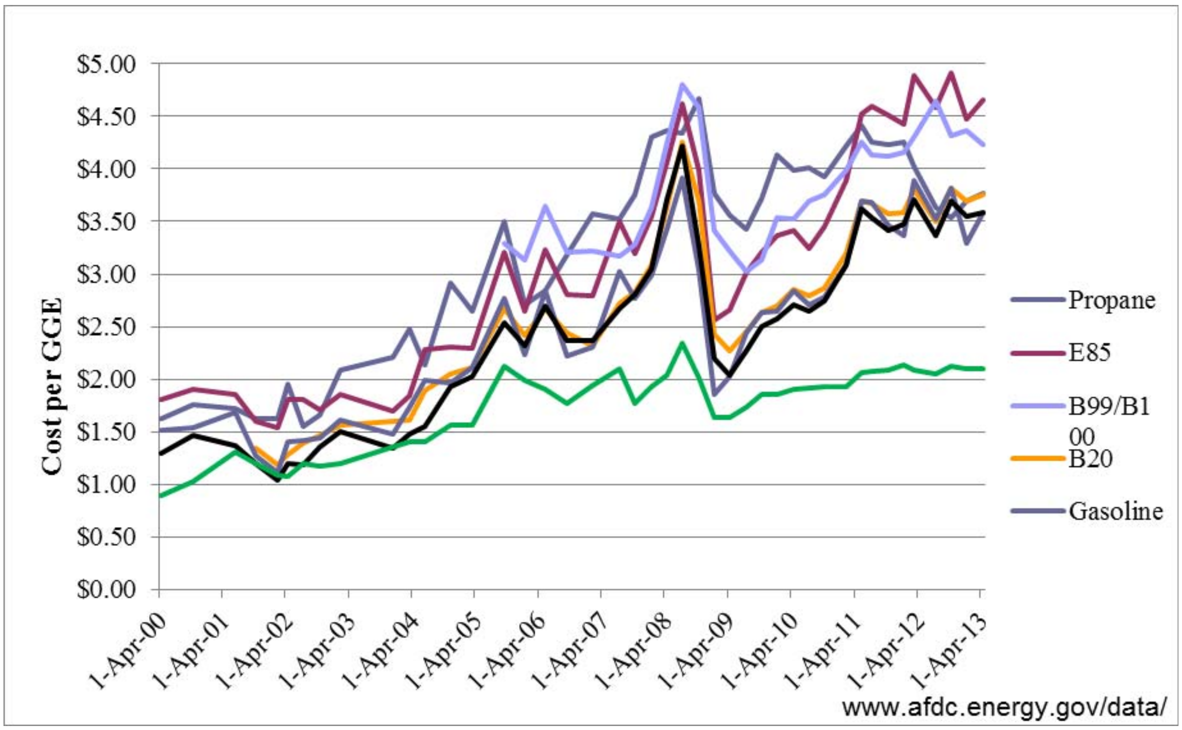


Figure A.2.1 Average Monthly Retail Fuel Prices Versus Time from April 2000 to April 2013

According to information collected by the Energy Information Administration (EIA) in 1999, world crude oil and natural gas reserves amount to about 1,000 billion barrels, and 5,140 trillion cubic feet respectively. North American reserves of oil and natural gas amount to about 6-7 percent and 5-6 percent of world reserves. The Persian Gulf region holds about two-thirds of the entire world's known oil reserves and the largest portion of petroleum imported by the U.S. comes from this region. The U.S. energy system and economy have been highly dependent on liquid fuels, and access to affordable liquid fuels has greatly contributed to the economic prosperity of the nation. However, the extent of U.S. reliance on imported oil has often been raised as a matter of concern over the past 40 years. According to Annual Energy outlook 2013 prepared by U.S. Energy Information Administration (EIA), net imports of petroleum and other liquid fuels as a share of consumption have been one of the most- watched indicators in national and global energy analyses. After rising steadily to 47 percent from 1950 to 1977, U.S. net import dependence declined to 27 percent in 1985. Between 1985 and 2005, net imports of liquid fuels rose again reaching a 60 percent mark in 2005. However, the trend toward growing U.S. dependence on liquid fuels imports has again reversed, with the net import share falling to an estimated 41 percent in 2012, and with EIA projecting further significant declines in 2013 and 2014. Recent analysis by EIA indicates that the world oil production peak may not occur for another 20 to 50 years. However, regardless of when the peak is reached, crude oil prices are likely to increase significantly in advance of peak production.

In a report to the Congress titled "Effects of the Alternative Motor Fuels Act CAFÉ Incentives Policy" prepared jointly by the U.S Department of Transportation, the U.S. Department of Energy and the U.S. Environmental Protection Agency (March 2002), it is stated the costs to the U.S. economy from a future oil price shock could be enormous with substantial macroeconomic impacts leading to a reduced U.S. economic activity by an average of over 2 percent per year for three to four years or more. Since the oil shocks of the 1970s and 1980s, the transportation sector remains overwhelmingly dependent on petroleum-based fuels unlike other energy using sectors which have introduced substitute fuels and fuel switching flexibility. The transportation sector currently accounts for approximately two-thirds of all U.S. petroleum use and roughly one-fourth of total U.S. energy consumption, making it vulnerable to sudden fuel price upsurges in world market. In light of these circumstances, much attention has been drawn to develop a robust energy policy to secure national interest and economic developments by reducing dependence on fuel imports. Apart from increasing native oil production, substitution of petroleum-based transportation fuels (gasoline and diesel) by non-petroleum-based fuels could act as a key means of reducing the vulnerability of the U.S. transportation sector to petroleum supply disruptions and hold down world crude oil prices. As a reasonable rule of thumb, a decrease in demand by 1 percent for petroleum based fuels by the U.S. is assumed to result in a 0.5 percent reduction in world oil price in the long run, although the actual impact will depend on precisely how OPEC responds.

A.2.1 Emerging Alternative Vehicle-Fuel Technologies

The motor vehicle industry is an ever flourishing industry catering to the desires and needs of human beings to travel, and move goods safely with efficiency. For centuries, petroleum based fuels (diesel and gasoline) have been the primary source of energy that drove these vehicles. Like all other resources, petroleum is neither inexhaustible nor available in all parts of the world. New and better technologies are being introduced every year leading to improved fuel efficiency and safety. Despite accomplishments of increased fuel efficiency by modern motor vehicles, the demand for petroleum based motor vehicle fuels has been on the rise. Increased economic activities are putting more and more commuters on the road resulting in increased demand and a consequent rise in fuel price. With a view to free motor vehicle users from future uncertain energy crisis, much effort has been diverted toward development of newer technologies to identify and harness energy from alternative sources to power motor vehicles. Such endeavors have produced a good number of alternatives to petroleum based fuels. Some of the promising alternative vehicle fuels along with their advantages and limitations to be used as in vehicles are discussed in the following sections.

A.2.1.1 Biodiesel

Biodiesel is a domestically produced cleaner burning alternative to petroleum based diesel that can be manufactured from vegetable oils, animal fats, or recycled restaurant grease for use in diesel vehicles. Usually a blend of biodiesel and petro-diesel is used as an alternative to diesel fuel in vehicles. It is nontoxic and biodegradable and can significantly reduce emissions and environmental pollution. Biodiesel can be used in conventional compression-ignition engines which run on petroleum based diesel. Though biodiesel is a promising alternative to petroleum based diesel, high production cost of biodiesel makes it more expensive compared to regular diesel. Uncontrolled production of biodiesel to reduce cost may result in decreased production in food crops and a consequent global increase in food price. Again, the cold-flow properties of biodiesel blends vary depending on the amount of biodiesel in the blend. The smaller the percentage of biodiesel in the blend, the better it performs in cold temperatures.

A.2.1.2 Electricity

Electricity is another alternative source of energy that is being used to power all-electric vehicles and plug-in hybrid electric vehicles. These vehicles can draw electricity directly from the grid and other off-board electrical power sources and store it in batteries. Hybrid electric vehicles use electricity to boost fuel efficiency. Although the use of electricity as the only energy source or in combination with conventional fuel apparently helps reduce emissions from the car, the production of electricity is not always clean (coal based power plants). Limited energy storage capacity is the most significant drawback for the utilization of electricity as an efficient source of alternative energy to power vehicles. Long charging times, limited range and large and expensive batteries are the downsides of using electric powered vehicles.

A.2.1.3 Ethanol

Ethanol is a renewable fuel made from corn and other plant materials. Ethanol-fueled vehicles run on a mixture of gasoline and ethanol. The most popular ethanol fuel blend is E85. The name reflects the proportions of 85 percent ethanol to 15 percent gasoline used in the fuel. This makes it an emissions-friendly fuel. There are an increasing number of alternative fuel cars now being supplied for this market. Ethanol is a potential alternative fuel but it does not cost less compared to gasoline. Ethanol cannot be transported by pipelines since it catches impurities and water which makes its transportation costly. Moreover, most U.S. ethanol plants are concentrated in the Midwest near the corn fields making transportation to oil refineries where it is blended with gasoline costlier. Also a large amount of fossil fuel is used to produce ethanol from food grains reducing overall benefits.

A.2.1.4 Hydrogen Fuel Cell

Hydrogen is a potentially emissions-free alternative fuel that comes from water and is therefore a renewable fuel with inexhaustible supplies and benefits in fuel cost. The exhaust from a hydrogen-fueled car is basically water, and is totally environment-friendly. Hydrogen fueled vehicles are very expensive to produce as the entire system is very fragile. In addition, hydrogen is a very explosive fuel and no complete solution has yet been found to the safely transport this fuel to the pump for distribution.

A.2.1.5 Propane

Propane or otherwise known as liquefied petroleum gas (LPG) or auto-gas is another potential alternative fuel that has been used worldwide as a vehicle fuel for decades. Propane has a high octane rating and excellent properties for spark-ignited internal combustion engines. It is non-toxic and presents no threat to soil, surface water, or groundwater. It is stored as a liquid in a tank pressurized to about 150 pounds per square inch. Lower maintenance cost is a prime reason behind propane's popularity for high-mileage vehicles. Because the fuel's mixture of propane and air is completely gaseous, cold start problems associated with liquid fuel are reduced. Although it has a higher octane rating than gasoline (104 to 112 compared with 87 to 92 for gasoline), and potentially more horsepower, it has a lower Btu rating than gasoline, which results in lower fuel economy.

A.2.1.6 Natural Gas (CNG and LNG)

Natural gas accounts for about a quarter of the energy used in the United States. About one-third goes to residential and commercial uses, such as heating and cooking; one-third to industrial uses; and one-third to electric power production. It is an odorless, nontoxic, gaseous mixture of hydrocarbons—predominantly methane (CH_4). This clean-burning alternative fuel can be used in vehicles as either compressed natural gas (CNG) or liquefied natural gas (LNG). Natural gas is sold in units of gasoline gallon equivalents (GGEs) based on the energy content of a gallon of gasoline. CNG is stored onboard a vehicle in cylinders at a pressure of 3,000 to 3,600 pounds per square inch. LNG is produced by purifying natural gas and super-cooling it to -260°F to turn it into a liquid. Because it must be kept at cold temperatures, LNG is stored in double-walled, vacuum-insulated pressure vessels. LNG is good for trucks needing a longer range because liquid is more dense than gas (CNG) and, therefore, more energy can be stored by volume in a given tank. LNG is typically used in medium- and heavy-duty vehicles. Short range and large storage tanks compared to traditional fuels are the primary drawbacks of using natural gas.

A.2.2 Impacts of Alternative Vehicle-Fuel Technologies on Uncertain Future Purchase Cost

Almost all alternative fuel technology requires modification of the conventional fuel motor vehicles (both engine and body) to enabling running on alternative fuels. The extent of modification is dependent on the particular type of alternative fuel under consideration. Again, some other alternative fuel technologies (electric cars) are based on operating principles totally different from conventional fuel engines. Regardless of the type of modification, whether it is a slight modification to the conventional fuel engine or a totally different propulsion system, a substantial cost is involved for utilizing alternative fuels as a substitute for conventional fuels. The popularity and impact of a particular alternative fuel technology on future purchases will be dependent mostly on its benefits compared to the additional price incurred for its acquisition. The time required to amortize this additional cost (compared to conventional fuel vehicles) may be considered as a most convenient and useful measure for estimating benefits. A lower amortization time than the expected life of a vehicle in the fleet indicates a net saving due to lower fuel costs compared to conventional fuel vehicles. However, the time required for the recovery of the additional cost is largely dependent on the price differential of the alternative fuel under consideration with conventional petroleum based fuels (diesel and Gasoline), the extent of the use of the vehicle (average annual mileage), and also on the additional cost itself.

Table A.2.1 shows overall nationwide average prices for conventional and alternative fuels for April 2013. This table illustrates the variation of alternative fuels relative to conventional fuels. On average, CNG is about $1.49 less than gasoline. On a per-gallon basis, E85 is about 29¢ less than gasoline and propane is about 86¢ less than gasoline. B20 prices are higher than regular diesel by about 12¢, while B99/B100 blends have a cost of about 30¢ per gallon more than regular diesel.

Table A.2.1 Overall Average Fuel Prices

Fuel Type	*Nationwide Average Price For Fuel*
Gasoline	$3.59
Diesel	$3.99
CNG	$2.10
Ethanol (E 85)	$3.30
Propane	$2.73
Biodiesel (B20)	$4.11
Biodiesel (B99-B100)	$4.29
Electricity	---

Source: Clean Cities Alternative Fuel Price Report. U.S. Department of Energy. April 2013

However, these fuels have differing energy contents per gallon. As a result the price paid per unit of energy content can differ somewhat from the price paid per gallon. Table A.2.2 illustrates the fuel prices from Table A.2.1 normalized to a price per gasoline gallon equivalent (GGE) and per diesel gallon equivalent (DGE) of energy (based on nominal lower heating values in BTU's per gallon of fuel from the Oak Ridge National Laboratory's Transportation Energy Data Book).

Table A.2.2 April 2013 Overall Average Fuel Prices on Energy- Equivalent Basis

	Nationwide Average Price in Gasoline Gallon Equivalents	Nationwide Average Price in Diesel Gallon Equivalents	National Average Price Between March 29 and April 12, 2013
Gasoline	$3.59	$4.01	$3.59/gallon
Diesel	$3.58	$3.99	$3.99/gallon
CNG	$2.10	$2.34	$2.10/GGE
Ethanol (E 85)	$4.66	$5.20	$3.30/gallon
Propane	$3.77	$4.20	$2.73/gallon
Biodiesel (B20)	$3.75	$4.19	$4.11/gallon
Biodiesel (B99-	$4.23	$4.72	$4.29/gallon
Electricity	---	---	$0.117/KWh

Source: Clean Cities Alternative Fuel Price Report. U.S. Department of Energy. April 2013.

Prices for the alternative fuels in terms of cost per-gallon equivalent (diesel or gasoline) are generally higher than their cost per gallon because of their lower energy content per gallon compared to diesel or gasoline as illustrated by Table A.2.2. However, consumer interest in alternative fuels generally increases when the alternative fuel price is less than the conventional fuel price and as the price differential per gallon increases, even if that differential does not directly translate to savings on an energy-equivalent basis. On the basis of relative fuel price considerations, advantages, and practical application limitations, the likelihood of the potential alternative fuel technologies affecting vehicle purchase cost in the near future has been explored and discussed in the following sections.

Biodiesel blends like B5, B20 and B99-B100 (5%, 20% and 99-100% biodiesel) can be used to run conventional diesel powered vehicles without any major modifications. In case of using higher blends, modifications like changing rubber made hoses with synthetic material is recommended since biodiesel is known to eat away at rubber. This provides a great advantage for using biodiesel blends in conventional diesel fuel vehicles without undergoing any substantial increase in purchase cost. However, the most significant factor retarding the use of biodiesel in place of petro diesel is its higher price on an energy equivalence basis, at least for the time being. As the price of petroleum based fuels continue to rise, biodiesel might become a popular alternative for petro-diesel at some point in time.

In case of electric powered vehicles, hybrid electric vehicles (HEVs) typically achieve better fuel economy and have lower fuel costs than similar conventional vehicles. For instance, the EPA combined city-and-highway fuel economy estimate for 2012 Honda Civic Hybrid model is 44 miles per gallon compared to the 32 miles per gallon for its conventional four cylinder automatic version. However, some HEV models use hybrid technology to boost power rather than efficiency and consequently do not provide improved fuel economy over similar conventional vehicles. Plug-in hybrid electric vehicles (PHEVs) and electric vehicles (EVs) can reduce fuel costs dramatically because of the low cost of electricity relative to conventional fuel. Due to total or partial reliance on electric power, their fuel economy is measured differently than conventional vehicles. Miles per gallon of gasoline equivalent (mpge) and kilowatt-hours (kWh) per 100 miles are common metrics. Depending on the nature of their utilization, light-duty EVs (or PHEVs in electric mode) can now a day exceed 100 mpge and can achieve 30-40 kWh per

100 miles. Although fuel costs for hybrid and plug-in electric vehicles are generally lower than for similar conventional vehicles, purchase prices can be significantly higher. Limited energy storage capacity, longer charging period, and shorter hauling range are some of the major challenges faced by this technology in becoming a successful replacement for conventional fuel vehicles.

Similar to biodiesel technology, ethanol and gasoline blends (E 10, E15 and E 85) can be used to run conventional gasoline vehicles through necessary modification (flex fuel vehicle). Low-level blends require no special fueling equipment and can be used in any gasoline vehicle. The high level blends like E85 require slightly different fueling equipment than petroleum fueling equipment, but the cost is higher. The conversion of a conventional gasoline vehicle to a flex fuel vehicle (FFV) requires extensive modifications throughout the fuel system and electronic engine-control system. FFVs are available nationwide as standard equipment with no incremental costs, making them an affordable alternative fuel vehicle option. Although power, acceleration, payload, and cruise speed are comparable whether running on ethanol or gasoline, the fuel economy is lower when FFVs run on ethanol. However, the appeal of ethanol (E85) as an alternative to gasoline is slim due to its higher price compared to gasoline on an energy equivalence basis.

Hydrogen powered fuel cell vehicles are considered to have the potential to revolutionize our transportation system since they are more efficient than conventional internal combustion engine vehicles. Fuel cell vehicles and the hydrogen infrastructure to fuel them are in an early stage of development. Significant efforts are being directed to make hydrogen-powered vehicles an affordable, environmentally friendly, and safe transportation option for the future.

Vehicles that can run on propane can either be obtained by conversion of conventional gasoline vehicles or purchased from original equipment manufacturers (OEMs). Two types of propane vehicles are available: dedicated and bi-fuel. Dedicated propane vehicles use only propane, while bi-fuel propane vehicles can run on either propane or gasoline. The power, acceleration, and cruising speed of a propane driven vehicle are similar to those of gasoline-powered vehicles. The driving range can be increased by the addition of extra storage tanks, but the additional weight will displace payload capacity. High octane rating (104 to 112 compared with 87 to 92 for gasoline) and low carbon and oil contamination characteristics of propane have resulted in greater engine life of up to two times of that of gasoline engines. Cold start problems associated with liquid fuel are also reduced due to the gaseous nature of the mixture. The cost to convert a light-duty vehicle from gasoline to propane use ranges from $4,000 to $12,000. The upfront costs to convert fleet vehicles to propane can be offset by lower operating and maintenance costs over the lifespan of the vehicles. However, the high price of propane compared to gasoline as shown in Table A.2.2 (on an equivalent gasoline basis) makes it less lucrative as a substitute for gasoline.

Natural gas vehicles (NGVs) can run on two forms of natural gas—CNG and LNG. Although limited light- and heavy-duty natural gas vehicles (NGVs) are available from original equipment manufacturers, qualified system retrofitters can also reliably convert many light-duty and heavy-duty vehicles for natural gas operation. There are basically three types of NGVs- dedicated, bi-fuel and dual fuel. Dedicated NGVs are designed to run on natural gas only, whereas bi-fuel vehicles can run on either natural gas or gasoline. The dual-fuel NGVs run on natural gas but use diesel fuel for ignition assistance. These dual-fuel vehicles are traditionally limited to heavy-duty applications. Light-duty vehicles typically operate in dedicated or bi-fuel modes, and heavy-duty vehicles operate in dedicated or dual-fuel modes. The choice of the form of natural gas depends primarily on the desired range of travel. Due to higher energy density of LNG compared to CNG, LNG is more-suited for heavy-duty vehicles like Class 7 and 8 trucks that need a greater range. Alternatively, CNG is a good choice for high-mileage, centrally-fueled fleets that operate within a limited area.

In the Annual Energy Outlook (AEO) 2013 Reference case, fuel switching to natural gas in the form of compressed natural gas (CNG) and LNG is already projected to achieve significant market penetration as a fuel for heavy-duty trucks. Domestic availability, widespread distribution infrastructure, low cost, and clean-burning qualities provides natural gas the upper hand as a promising alternative transportation fuel. Even after the substantial costs of liquefaction or compression, fuel costs for LNG or CNG are expected to be well below the projected cost of conventional gasoline and diesel fuel on an energy-equivalent basis. A large fuel cost advantage may motivate a significant number of operators to offset the considerably higher acquisition costs of vehicles equipped to use natural gas in addition to offsetting disadvantages such as reduced maximum range without refueling, scarcity of refueling stations, reduced payload capacity in certain applications, and an uncertain resale market for vehicles using alternative fuels.

Only a few light-duty dedicated natural gas vehicles are available directly from major original equipment manufacturers. Honda manufactures the only natural gas-driven sedan: Civic natural gas. GMC Sierra and Chevy Silverado are the two natural gas enabled light-duty trucks manufactured by General Motors Corporation. The Honda Civic natural gas version costs about $5,650 more than its conventional fuel equivalent Civic EX version. Whereas, both the GMC Sierra and Chevy Silverado cost an additional $11,000 for a bi-fuel CNG version compared to conventional gasoline version. Costs of converting conventional fuel driven vehicles to natural gas driven vehicles by qualified system retrofitters vary depending on a number of factors such as original engine type, original fuel type and desired fuel tank capacity. The usual range of conversion cost was found to be within $5,000 to $12,000. For LNG, the conversion cost varies between $8,000 and $12,000 as quoted by qualified system retrofitters. Table A.2.2 shows that on the basis of equivalent energy, natural gas has an overall price advantage over conventional fuels (diesel and Gasoline). For the state of Texas, the price of CNG per gasoline gallon equivalent is about $2.25 (with a 15¢ state tax) compared to a gasoline price of about $3.50 per gallon in April 2013 which results in a saving in fuel cost of about $1.25 per gasoline gallon equivalent. Large savings in fuel cost may act as an incentive to offset high purchase or conversion costs and make natural gas a feasible future alternative fuel option. The Feasibility of natural gas becoming a potential future alternative to conventional fuels is therefore highly contingent upon the relative price differential and average annual mileage driven. The higher the price differential, the lower the time required to amortize the initial purchase or conversion cost. To get a better understanding of the relationship between fuel price differential and amortization time, graphs of price differential against amortization time for a combination of vehicle and natural gas options are displayed next. Figure A.2.2 shows the cost amortization time against CNG fuel price differential for sedans for an annual interest rate of 0 percent and 3 percent. An initial acquisition cost of $5,000 was considered for sedan cars. With an assumption of 12000 annual vehicle miles driven at a 28 miles per gallon (gasoline) average fuel economy and for a current fuel price differential of $1.25, the time required to amortize the additional cost is about 11 years at an annual interest rate of 3 percent.

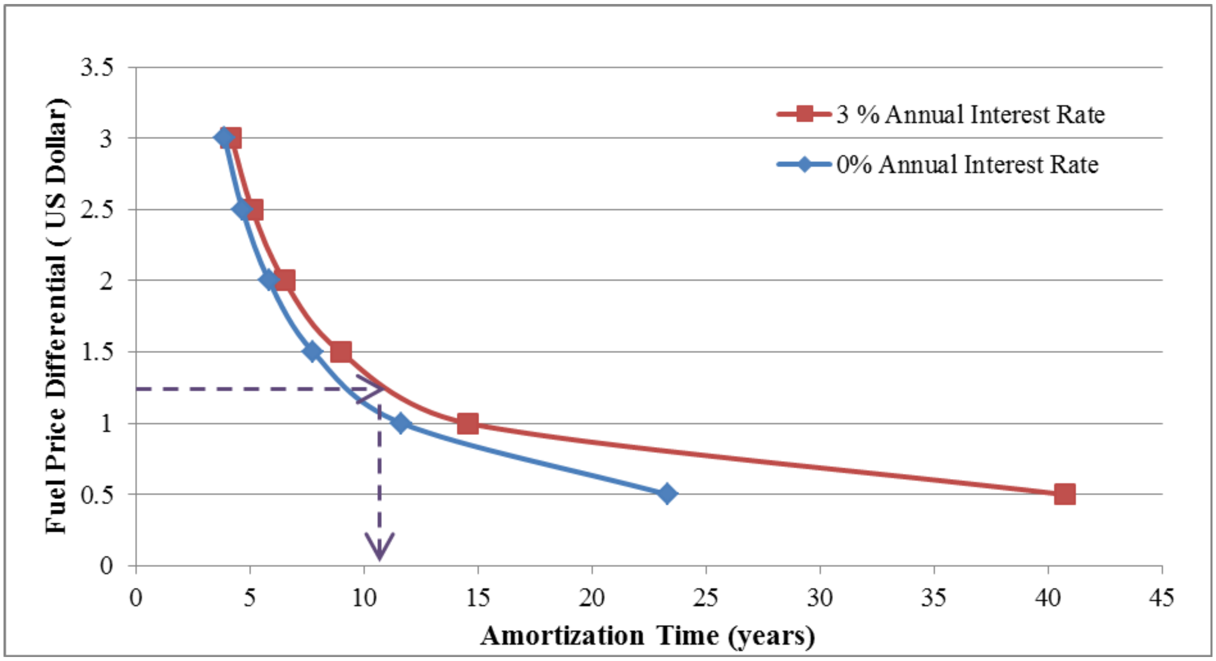


Figure A.2.2 Price Differential of CNG With Respect to Gasoline Versus Cost Amortization Time for Sedan Cars

Similarly for light duty trucks, the time required to recover the initial extra cost of $12,000 (assumed) with an average annual mileage of 12000, an overall fuel economy of 18 miles per gallon of gasoline and at the current fuel price differential of $1.25 is about 20 years for an annual interest rate of 3 percent. Figure A.2.3 shows the cost amortization time for light-duty trucks for varying fuel price differentials.

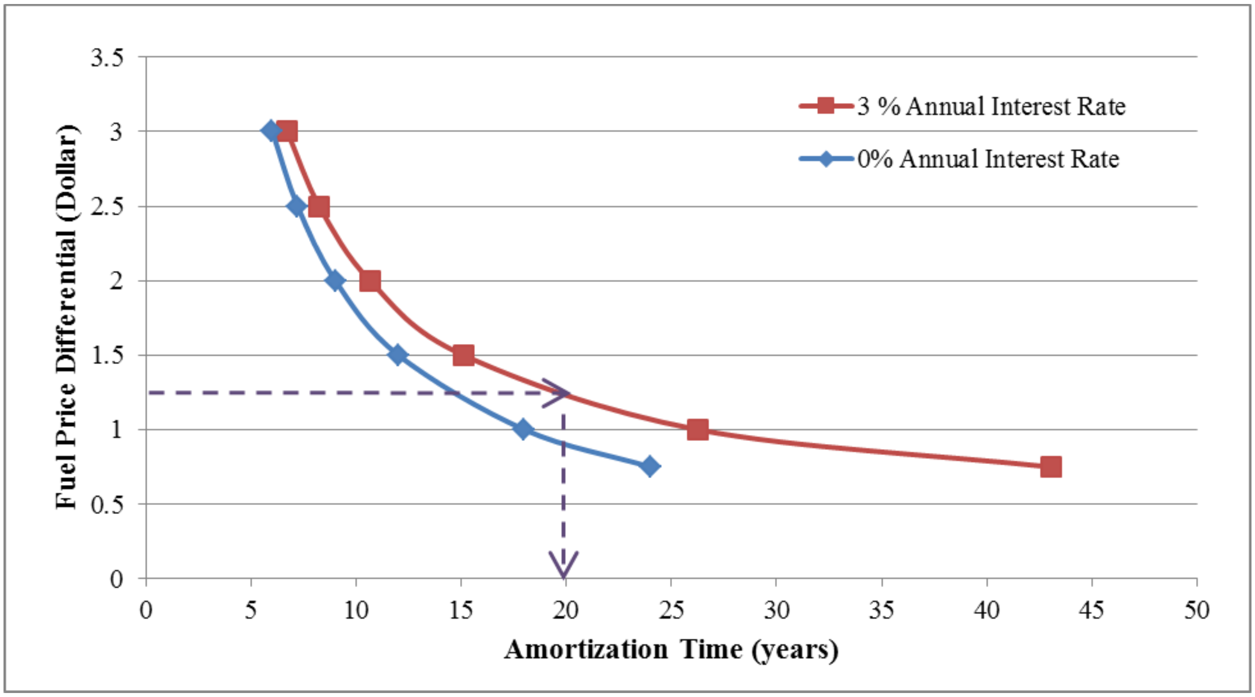


Figure A.2.3 Price Differential of CNG With Respect to Gasoline Versus Cost Amortization Time for Light Trucks

Unlike CNG, LNG is not sold as gasoline gallon equivalent. LNG has an energy density of about 60 percent of its conventional counterpart diesel. The current retail price of LNG is around \$2.75 per gallon. When converted to equivalent energy, LNG costs about \$4.58 per diesel gallon equivalent compared to \$3.99 per gallon of diesel. A \$0.5 tax rebate on LNG brings it close to but still about 8¢ higher than diesel on an energy equivalent basis. The higher retail price of LNG compared to CNG is because of its special storage and transportation requirements. However, the wholesale price of LNG is about half the retail price. Figures A.2.4 and A.2.5 show cost amortization time against fuel price differential for LNG enabled heavy-duty vehicles.

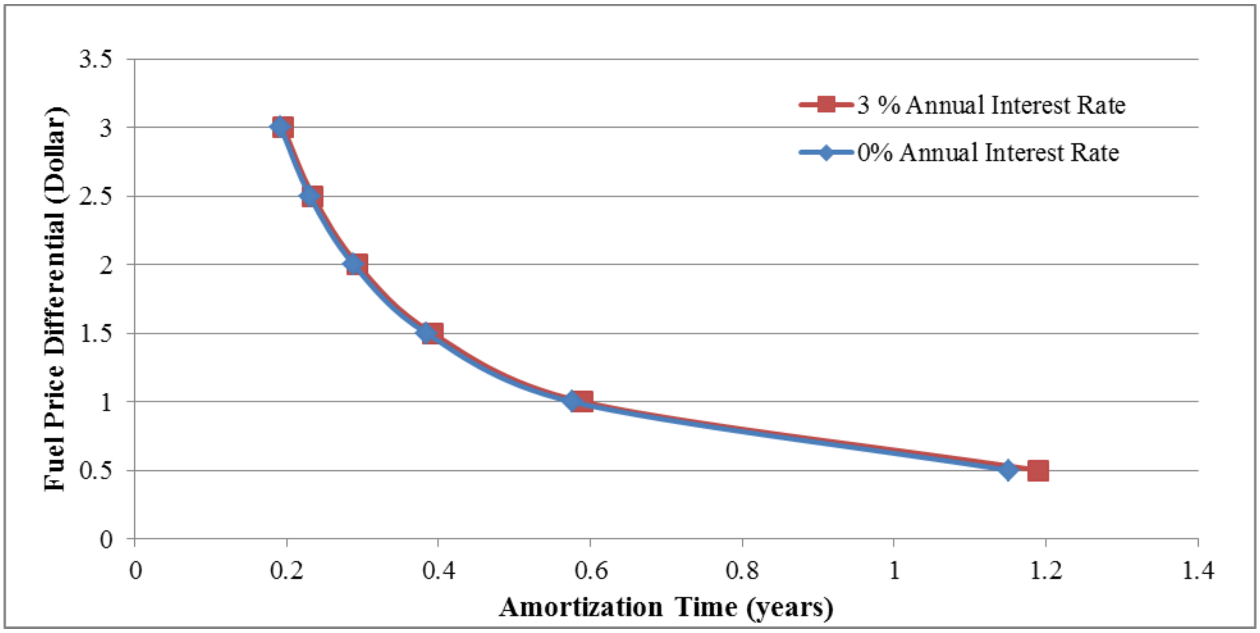


Figure A.2.4 Fuel Price Differential of LNG With Respect to Diesel Versus Cost Amortization Time for Heavy Duty Vehicles for a Conversion Cost of US$8000

In Figure A.2.4, the low end of conversion cost of $8,000 was considered while the high end of conversion cost of $18,000 was considered in Figure A.2.5. Average annual mileage of 50,000 and an overall fuel economy of 6 miles per gallon (diesel) were considered conservative estimates for heavy-duty vehicles. It is evident from Figures A.2.4 and A.2.5 that greater utilization of heavy-duty vehicles (higher annual average mileage) results in lower amortization time compared to light vehicles for the same level of fuel price differential. Due to higher retail price of LNG, it appears that there is no net savings under current conditions. However, organizations with large vehicle fleets can arrange for their own storage and distribution facility and purchase LNG at the wholesale price. In this way, a net savings in fuel cost can be achieved making LNG use profitable in the long run.

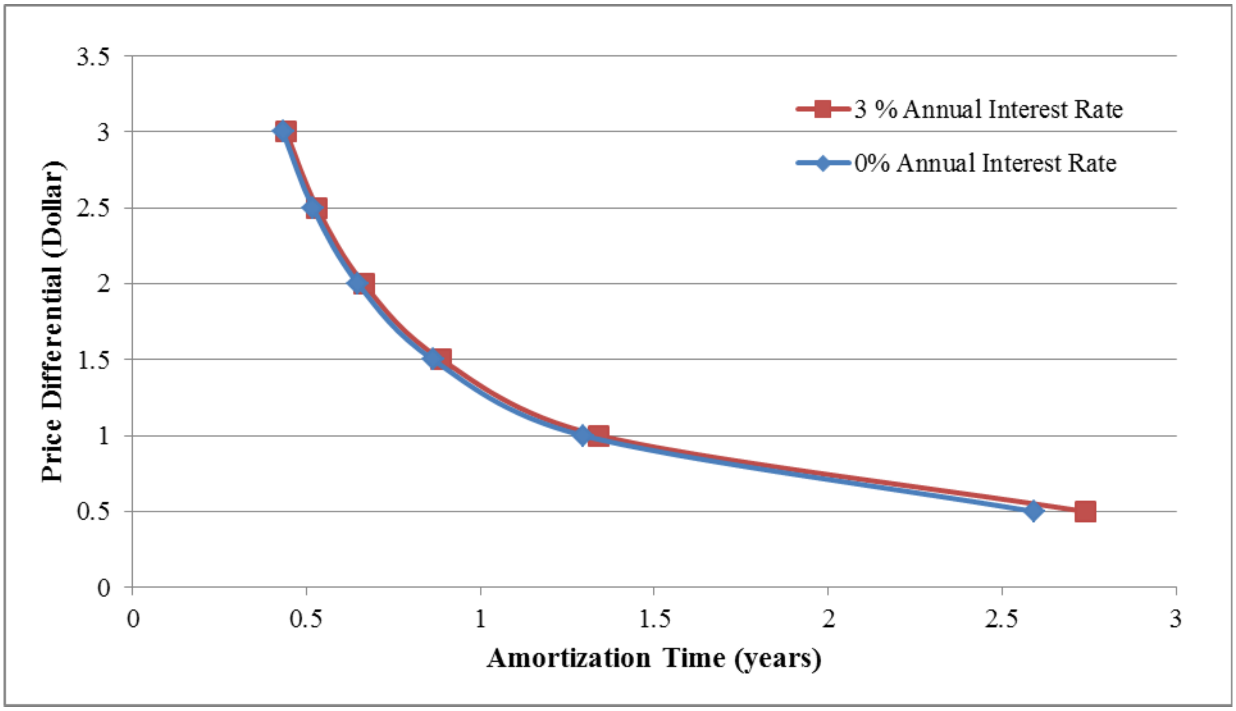


Figure A.2.5 Fuel Price Differential of LNG With Respect to Diesel Versus Cost Amortization Time for Heavy Duty Vehicles for a Conversion Cost of $18,000

Although natural gas has a price advantage over conventional petroleum fuels, the current price differential is not sufficient enough to beneficially recover the additional cost of acquisition of new natural gas vehicles or of converting existing vehicles to operate on natural gas within the limited expected life of a vehicle in the TxDOT fleet. However, if the price of petroleum based fuels (diesel and gasoline) continue to increase following the current trend, the price difference between natural gas and the petroleum fuels may become sufficient enough to advocate the use of natural gas vehicles in future.

A.2.3 Summary

The original strategy for forecasting the purchase cost was based on selecting the best-fit model from a series of linear and nonlinear statistical models created from the available historical data. This approach resulted in some projections yielding a decreasing, and in some cases negative, forecasted purchase cost. To solve this problem, a number of strategies were created and tested in order to establish an algorithm for the software.

These strategies included implementation of a factor of the inflation rate (multiplied by the purchase cost) in place of a statistical model, use of MSRP in place of historical purchase cost, addition of commodity price index variables as predictors, utilization of moving averages for purchase cost, examination of other equations with a high quality of fit (high R-square value), and creation of simple linear models. Ultimately, it was decided that using a simple linear model with a series of threshold tests, designed to ensure a quality forecast, would be applied as the primary option for the software algorithm. It was determined that a linear model would be the most appropriate model due to its propensity to have a positive slope over a large data set, its simplicity of robust application in algorithm form, consistency with future additions to the data sets, and provision of a relatively good fit overall for any trends in the data.

As a contingency, a secondary option utilizing a multiple of the inflation rate, to be applied if the linear model fails the threshold tests, was also implemented as part of the software algorithm. This factor was decided to be one-half of the inflation rate, to be multiplied by the current year's purchase cost to establish the value for the subsequent year. The algorithm, including a secondary outlier removal process, was then coded into the software so that the updated cost forecasts could be input into the optimization engine and subsequently tested for consistency. The results of these tests indicated that the algorithm was performing appropriately, and the forecasted purchase costs for all classcodes would now be increasing over the 20-year horizon.

Recent unwarranted fuel price (crude oil) hikes due to instability of world fuel market and heavy dependency of U.S. transportation sector on imported fuel has become a matter of great national concern for the policy makers. Along with increasing native oil and gas production, alternative avenues are also being explored to reduce this dependency to an acceptable level. In this effort, alternative vehicle fuel technologies have gained much attention, more than ever before. Supported by national policies and directives, renewed efforts are being directed for the development and promotion of sustainable and economically feasible alternatives to conventional fuels (diesel and gasoline).

As a part of this of this task, six potential alternative fuel technologies-biodiesel, electricity, ethanol, hydrogen fuel cells, propane and natural gas were identified along with their advantages and drawbacks in an effort to evaluate their impacts on future uncertain purchase cost. It was observed that most of the technologies required at least some form of modification to the original conventional fuel vehicles in order to operate them on alternative fuels involving additional cost. Again, some of the technologies are based on completely different propulsion systems (electric, Hydrogen fuel cells) and are highly priced compared to conventional vehicles due to limited quantity production. In order for any alternative vehicle fuel technology to gain popular acceptance and motivate vehicle users to endure additional acquisition cost, there must be some forms of incentive. Savings in terms of fuel cost resulting in net economic benefits in the long run is one such incentive. Also, in order to make considerable savings in fuel costs, the price difference between conventional fuel and the alternative fuel must be substantial enough for quick recovery of the increased acquisition cost. Based on average retail fuel price in the U.S. for April, 2013, it was observed that biodiesel, ethanol and propane are sold at a higher price compared to conventional fuels (diesel and gasoline) on an equivalent energy basis making them economically unattractive. Hydrogen fuel cells are still in the developing stage making them infeasible for field use. Electric vehicles have great potential because of the low cost and high availability of electricity. However, expensive and heavy batteries, long charging times, short operating distance and high initial price are some of the major challenges for this technology. Between the two varieties of natural gas, CNG is currently priced lower compared to gasoline on an energy equivalent basis. Although this provides CNG users a price advantage of about $1.25, it would take about 11 years for sedans and 20 years for light-duty trucks (more than the expected life of a vehicle in TxDOT fleet) to recover the additional acquisition cost. The other form of natural gas, LNG, is currently sold at a higher retail price compared to diesel on an equivalent energy basis though the wholesale price is half of the retail price. Organizations with large vehicle fleet can make arrangements for their own storage and distribution facilities and obtain LNG at a wholesale price making it economically beneficial in the long run.

Chapter A.3. Estimating Down Time and Related O&M Costs

The purpose of this work was to estimate down time costs unique to each equipment classcode in the Texas Department of Transportation (TxDOT) TERM database and investigate operations and maintenance (O&M) costs coupled with TxDOT's recent fleet rightsizing efforts. The original approach for estimating down time costs was to use a constant rate across all classcodes; however, this was determined to be insufficient for properly establishing subsequent O&M costs, which are based partly on down time costs. The O&M costs as part of project 0-6412 were based on this strategy and development of a new methodology for forecasting O&M costs included a change in down time rates. Furthermore, it was determined that the models used to forecast O&M costs were causing issues with the equipment replacement optimization (ERO) decision-making process and modifications to the strategy were developed and, ultimately, have been chosen for implementation.

The approach for estimating down time costs as part of project 0-6412 involved using a universal down time rate for all classcodes. This rate was set at $25 per hour and was multiplied by the number of annual down time hours to calculate annual down time cost. This approach was determined to be limited due to the fact that different vehicle types incur a different penalty, in terms of cost, when they are out of service. The true down time costs vary across the different TxDOT classcodes. Therefore, a down time rate was established for each classcode based on information obtained regarding the appropriate estimation of down time costs, along with techniques used to determine an hourly rate for different vehicle and equipment types. Although down time rates are used in the calculation of O&M costs, their proper estimation was only one part of evaluating the O&M costs used for the ERO process.

Based on the TxDOT TERM data, the research team developed five different types of models (including Linear/Polynomial/Logarithm/Exponential/Power models) in TERM2 as a result of project 0-6412 to forecast O&M costs using equipment age as the independent variable. Although the models seemed to perform well from a technical perspective, some O&M cost forecasts did not yield intuitive results and caused inadvertent impacts to the ERO decision process. For some classcodes, even the best forecasting model derived from historical O&M data can yield negative forecasts for O&M cost due to decreasing utilization of vehicles and equipment as they age. The research team explored modifying some of the O&M data, implementing a minimum annual O&M cost and minimum O&M cost per unit of utilization (mile or hour) for all classcodes, as well as strategies involving thresholds for choosing a statistical model versus using the historical data. After determining a feasible way to estimate the future O&M costs was identified, it was incorporated into the TERM2 equipment replacement optimization software. All potential strategies have been comprehensively tested and validated.

A.3.1 Introduction

The original strategy for estimating down time was to use one universal rate for classcodes in the TxDOT TERM database. However, this estimate was limited, as different vehicle types are likely to incur different costs due to being out of service. Therefore, a unique rate was established for each individual classcode based on recommendations gathered from a review of relevant literature. Since down time is part of the overall O&M costs for each equipment unit, its proper estimation was a critical component in establishing forecasts for O&M costs.

It was found that the strategy for forecasting the O&M costs developed for project 0-6412 required some modifications, in a similar manner to that of the purchase costs. The original approach involved development of multiple statistical models to forecast equipment purchase costs. Upon implementation of the above strategy, some forecasted O&M costs were found to be much higher or lower than expected, and in some extreme cases, negative. This prompted the research team to do a full review of the forecasts for each classcode. It was discovered that several issues involving forecasted O&M costs were prevalent. This finding led to the development of a strategy intended to create more robust forecasts of O&M costs for all classcodes and associated circumstances. The estimation of down time and obstacles discovered using the original O&M cost forecasting approach, as well as the development of an alternate strategy and its subsequent implementation into the software package, are further described in the following sections.

A.3.2 Estimating the Cost of Down Time

In an effort to improve the ability of the optimization engine to develop a replacement plan for equipment, all life-cycle costs were considered. This led to the investigation of the cost of down time. It was determined that a simple, universal estimate for down time rate might not be sufficient to cover the extensive range of equipment types and subsequent failure scenarios. Therefore, a number of references were reviewed for additional information about estimating down time costs for equipment fleets. It was discovered that estimating the cost of down time can have a profound impact on decisions relative to fleet management. Furthermore, a number of strategies were uncovered from reports conducted for the United States (US) Army, as well as local governments.

In a study conducted for the US Army by Virginia Tech University, costs related to down time were investigated, as well as strategies for their estimation (Fuerst et al., 1991). It was determined that down time costs could be divided into two categories: tangible costs, and consequential costs. Tangible costs were described as those associated directly with the breakdown of a piece of equipment or vehicle, including labor, materials, and repair resources. These costs were described as relatively simple to track. On the other hand, consequential costs were identified as those associated with a failure that impacted an entire project, department, or organization. These costs are much more difficult to quantify accurately and require more information to effectively monitor. It was offered that a rough estimate of consequential costs could be obtained for a vehicle by multiplying the percent of down time by the number of planned hours of use and the hourly cost of replacement or rental. It was concluded that effective fleet management requires a balance between capital costs versus those costs associated with operating at an inferior level.

It was determined that to more accurately estimate the costs associated with vehicle or equipment failure, the hourly cost of resources affected by the failure, the time necessary to react, and the frequency of failure need to be taken into account where failure causes system-wide impacts (Fuerst et al., 1991). A series of formulas were developed as part of the study for estimating the cost components, including information relative to impact lag, impact duration, and cumulative costs. The procurement of substantial information for each failure would be required for the most accurate estimation of down time costs. However, implementing the strategy at a low level of complexity could be accomplished for monitoring a particularly large fleet. Ultimately, the most crucial information required for estimating down time costs for each vehicle or piece of equipment was identified to be the number of breakdowns, the number of hours broken down each month, and the number of hours in working condition each month.

Another study was completed by the Rand Corporation for the US Army (Pint et al., 2008). The study purpose was implementing a fleet management strategy for Army rubber-wheeled vehicles at bases throughout the world. At the heart of the report was development of statistical models to assess vehicle age and other predictor variables relative to repair costs and down time. These models were implemented in an optimal vehicle replacement model. The study investigated approximately 21,700 vehicles, including fifteen types at twelve locations. Of primary interest for prediction of repair costs and down time were variables for vehicle age, annual usage, odometer reading, location, and type of vehicle. Overall, it was determined that repair costs and down time increase with vehicle age, a trend that tapered off with older vehicles. A similar but weaker relationship was found using vehicle usage as a predictor.

It was noted in the report that the models required an estimate for the cost of down time and that labor data associated with mission critical failures was available (Pint et al., 2008). Down time, as estimated with respect to vehicle age and usage, was investigated by determining the number of days a vehicle was inoperative for each repair and computing the average annual down time. Repair costs were implemented as an annual average amount for parts and labor. In all, down time was determined to increase with age, as represented by the probability of down time exceeding zero, and was also discovered to be influenced by location. The cost of down time was defined as the cost of being without a piece of equipment and was estimated using the cost of renting a replacement vehicle. Furthermore, this cost was augmented by a risk factor. The daily rental cost was multiplied by a risk factor of three if the identified failure prevented completion of a mission. If the failure was not deemed to be mission-critical, typically based on the availability of another fleet vehicle, then only the daily rental rate was utilized as the estimate. It was determined that the use of a risk factor in the estimation of down time costs had a large impact on the results obtained by the optimal replacement model.

Further review of fleet management and the related cost of down time led to the examination of several reports for local governments. The first was a fleet management audit for the City of Palo Alto, California (2010). It was found that the city recently saved millions of dollars by freezing the replacement of non-urgent fleet vehicles. The city further improved efficiency by developing a strategy for adequately funding fleet repair and maintenance. It was also determined that the city needed to better manage their repair parts inventory. As an overall strategy for fleet management, the report outlined a number of recommendations. The report recommended revising policies to develop cost-effective utilization criteria and to clarify replacement criteria and guidelines for take-home use of vehicles. Additional recommendations included rotating vehicles between departments to better balance their utilization, freezing the replacement of under-utilized vehicles, making sure vehicles identified for replacement were actually removed from the fleet, and renting vehicles when possible. These recommendations where shown to require complete data about city vehicles, including an up-to-date database of pooled vehicles identifying their availability.

Another audit report was examined involving a multi-year review of fleet management for Clark County, Washington (2004). Again, it was recommended to eliminate underutilized vehicles (less than 6,000 mi per year) and to investigate why "replaced" vehicles were often retained. It was determined that these issues contributed to a fleet that was losing value without the benefit of extensive use. In particular, the pooled vehicles were significantly underutilized and it was recommended to either decrease the size of the pool and rent vehicles as required or develop a strategy to increase utilization, including development of a cost-per-mile performance measure for vehicles and implementation of a minimum mileage standard.

A fleet management study for the City of Chattanooga, Tennessee (2002) was also reviewed. As identified by others, the need for a detailed database of information about the fleet was recommended for future reference. Additional recommendations included monitoring the quality of maintenance and repair practices, making preventative maintenance a priority, and determining the life-cycle costs relative to new equipment purchases, including availability of repair parts and familiarity of maintenance staff with equipment.

The acclaimed success of the fleet management department for the City of Winnipeg, Manitoba, Canada was also investigated (St. George, 2007). It was determined that the city's vehicle fleet was oversized and that many older vehicles were frequently in repair, requiring additional vehicles to cover the excessive down time. The city decided to upgrade to a newer, more reliable fleet and emphasize preventative maintenance. Through the process, the city adopted life-cycle cost management practices to help track purchases, repairs, and maintenance.

The investigation of fleet management and the cost of down time from the various reports resulted in the identification of several underlying themes. The reports underscored the importance of developing a detailed and up-to-date database for both fleet vehicles and available repair parts. The reports demonstrated the importance of preventative maintenance and the quality of services and repairs. Issues were also frequently identified with respect to the underutilization of vehicles and accurately accounting for life-cycle costs. Furthermore, the accurate estimation of down time costs was determined to be imperative for developing an optimal vehicle replacement strategy.

The reports conducted for the US Army identified a number of strategies for estimating down time cost. These strategies could involve specific information about fleet operations, possible failures, and the costs or impacts associated with those failures, or they could involve a minimal amount of information including the number and length of down time related events. However, both reports also identified the use of equipment or vehicle rental rates as an estimate for down time. This would result in an estimate that varies with the type of equipment in repair. While this doesn't involve estimating labor expenses and other consequential costs, a risk factor could be implemented as a simplified approach to account for those costs which are difficult to quantify.

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

The rental rate was chosen as an adequate assessment of down time cost based on the established precedence for its use and due to the limited information available relative to down time in the TxDOT database. The information provided identifies only the number of annual, down time hours incurred for each vehicle. To accomplish the task of assigning a down time cost, the rental rate for each classcode was determined using information obtained from various sources in the equipment and vehicle rental industry. An appropriate match and subsequent rental rate was found for many of the classcodes. However, several rates had to be estimated based on similar vehicle types or for equipment assigned tasks of similar significance. In the end, a daily rental rate was established for 197 classcodes found in the database. An hourly rental rate was also estimated from the daily rate for consistency with the information provided in the database regarding down time (hours).

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

The rental rates and risk factors were reviewed and approved by the TxDOT fleet manager prior to implementation into the optimization software. It should be noted that the finalized down time rates are provided in Excel format in the input folder as part of the program's file structure. This file can be reviewed and the rental rates, risk factors, and subsequent down time rates manually adjusted by the fleet manager, as deemed appropriate in the analysis process. Figure A.3.1 shows an image of the editable Excel file.

	A	B	C	D	E
1	Code	Daily Rate	Base Hourly Rate	Risk Factor	Adjusted Hourly Rate
2	1010	650	82	1	82
3	1020	650	82	1	82
4	1030	865	109	1	109
5	1040	1500	188	1	188
6	1050	650	82	1	82
7	2000	350	44	1	44
8	10010	550	69	2	138
9	10020	450	57	2	114
10	11010	835	105	3	315
11	12010	200	25	2	50
12	12020	350	44	2	88
13	12030	835	105	2	210
14	12040	835	105	2	210
15	13010	835	105	2	210
16	13020	450	57	2	114
17	14000	250	32	2	64
18	16000	400	50	2	100
19	17000	550	69	2	138
20	18000	700	88	2	176
21	19000	1000	125	3	375
22	19010	1500	188	3	564
23	20020	75	10	1	10
24	20030	75	10	1	10
25	25010	75	10	1	10

Figure A.3.1 Editable Excel Table with Risk Factors and Down Time Rates

The above figure shows a portion of the Excel file containing the derived values, including: code (equipment classcode), daily (rental) rate, base hourly (rental) rate, risk factor, and adjusted down time rate. The established rental rates along with the risk factors for all the 197 equipment class codes are listed in Table A.3.1 below.

Table A.3.1 Recommended Down Time Costs and Risk Factors for All 197 Classcodes

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
1	1010	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, TO 29', INC TRUCK	$650	$82.00	1
2	1020	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 30-39', INC TRUCK	$650	$82.00	1
3	1030	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 40-59', INC TRUCK	$865	$109.00	1
4	1040	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, 60' +, INC TRUCK	$1,500	$188.00	1
5	1050	AERIAL PERSONNEL DEVICE, TRUCK MOUNTED, MILEAGE	$650	$82.00	1
6	2000	AERIAL PERSONNEL DEVICE, TRAILER MOUNTED	$350	$44.00	1
7	10010	ASPHALT BOOSTER TANK, TRAILER MOUNTED	$550	$69.00	2
8	10020	ASPHALT BOOSTER TANK, TRUCK MOUNTED, INC. TRUCK	$450	$57.00	2
9	11010	ASPHALT DISTRIBUTOR, TRUCK MOUNTED, (INCLUDES TRUCK)	$835	$105.00	3
10	12010	ASPHALT MAINTENANCE UNIT, 600 GAL, TRAILER MOUNTED	$200	$25.00	2
11	12020	ASPHALT MAINTENANCE UNIT, 1000 GAL, TRAILER MOUNTED	$350	$44.00	2
12	12030	ASPHALT MAINTENANCE UNIT, TRUCK MOUNTED	$835	$105.00	2
13	12040	ASPHALT MAINTENANCE UNIT, DUMPBODY CONTAINED	$835	$105.00	2
14	13010	ASPHALT POTHOLE PATCHER, TRUCK MOUNTED	$835	$105.00	2
15	13020	ASPHALT POTHOLE PATCHER, TRAILER MOUNTED	$450	$57.00	2
16	14000	ASPHALT MELTING KETTLE (HTR), TRAILER MOUNTED	$250	$32.00	2
17	16000	ASPHALT TANK CAR HEATER-CIRCULATOR	$400	$50.00	2
18	17000	ASPHALT TRANSFER TANK, TRAILER MOUNTED	$550	$69.00	2
19	18000	ASPHALT RECYCLING MACHINE, PORTABLE	$700	$88.00	2
20	19000	ASPHALT RECLAIMER/STABILIZER, CLASS I, SP, < 94.5 CUT WIDTH	$1,000	$125.00	3

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
21	19010	ASPHALT RECLAIMER/STABILIZER, CLASS II,SP, GREATER THAN 94.5 CUT WIDTH	$1,500	$188.00	3
22	20020	AUTOMOBILES, SEDAN, 100 THRU 112.9 IN. WHEELBASE			1
23	20030	AUTOMOBILES, SEDAN, 113 IN. WHEELBASE AND GREATER	$75	$10.00	1
24	25010	AUTOMOBILES, STATION WAGONS, UP TO 112.9 IN. WHEELBASE			1
25	26010	BUS	$800	$100.00	1
26	34000	CHIPPER, BRUSH	$200	$25.00	1
27	35000	CHIPPER, TREE, PORTABLE WITH HYDRAULIC GRAPPLE ARM FEEDER	$400	$50.00	1
28	36000	CLEANING UNIT, HIGH PRESSURE WATER TYPE, 10000 PSI MINIMUM	$1,000	$125.00	1
29	42000	CORE DRILL, PAVEMENT/CONCRETE SPECIMEN, TRUCK MOUNTED	$800	$100.00	2
30	44000	EARTH BORING MACHINE, TRUCK MOUNTED (INCLUDES TRUCK)	$1,200	$150.00	2
31	50000	CRANE,BRIDGE INSPECTION/MAINT TRUCK MOUNTED (INCLUDES TRUCK)	$3,500	$438.00	2
32	50010	CRANE,BRIDGE INSPECTION/MAINT TRAILER MOUNTED	$300	$38.00	2
33	52010	CRANE, CARRIER MOUNTED, CABLE OR TELESCOPING	$2,500	$313.00	2
34	52020	CRANE, CRAWLER TYPE, CABLE CONTROL	$1,750	$219.00	2
35	54000	CRANE, TELESCOPING BOOM, TRUCK MOUNTED (INCLUDES TRUCK)	$1,000	$125.00	2
36	56000	CRANE, YARD/INDUSTRIAL, SELF PROPELLED	$720	$90.00	2
37	64000	DYNAMIC DEFLECTION SYSTEM, TRAILER MOUNTED	$200	$25.00	2
38	70010	EXCAVATOR, HINGED OR TELESCOPING BOOM, CRAWLER TYPE	$650	$82.00	2
39	70020	EXCAVATOR, HINGED BOOM, PNEUMATIC TIRED CARRIER			2
40	75010	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS I	$165	$21.00	2

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
41	75020	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS II	$700	$88.00	2
42	75030	EXCAVATOR, TELESCOPING BOOM, CARRIER MOUNTED, CLASS III	$1,300	$163.00	2
43	80000	FORKLIFT, ELECTRIC	$165	$21.00	1
44	85010	FORKLIFT, ENGINE DRIVEN, UP TO 3,999 LB CAPACITY			1
45	85020	FORKLIFT, ENGINE DRIVEN, 4,000 LB AND OVER CAPACITY	$290	$37.00	1
46	86000	FORK LIFT, ROUGH TERRAIN			1
47	88000	GENERATOR, 100 KW AND GREATER	$400	$50.00	1
48	90010	GRADER, MOTOR, CLASS I, UP TO 109 H.P.	$400	$50.00	2
49	90020	GRADER, MOTOR, CLASS II, 110-134 H.P.	$450	$57.00	2
50	90030	GRADER, MOTOR, CLASS III, 135-149 H.P.	$525	$66.00	2
51	90040	GRADER, MOTOR, CLASS IV, 150 H.P. AND GREATER	$575	$72.00	2
52	100000	GUARDRAIL STRAIGHTENING MACHINE	$350	$44.00	2
53	110010	LOADER, CRAWLER, UP TO 1.9 CU.YD. CAPACITY	$800	$100.00	2
54	110020	LOADER, CRAWLER, 2 CU. YD. CAPACITY AND GREATER			2
55	115000	LOADER, PNEUMATIC TIRED, SKID STEER	$175	$22.00	2
56	115010	LOADER, PNEUMATIC TIRED, UP TO 1 1/2 CY	$190	$24.00	2
57	115020	LOADER, PNEUMATIC TIRED, 1 1/2 CY			2
58	115030	LOADER, PNEUMATIC TIRED, 2 CY	$350	$44.00	2
59	115040	LOADER, PNEUMATIC TIRED, 2 1/2 AND 3 CY	$450	$57.00	2
60	115050	LOADER, WINDROW	$350	$44.00	2

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
61	122000	MIXER, CONCRETE, TRUCK MOUNTED	$800	$100.00	2
62	124000	MIXER, LIME SLURRY, MUD JACK, TRAILER MOUNTED	$70	$9.00	2
63	130030	MOWER, LIFT OR TRAIL TYPE,COMB FLAIL,14 FT. OR GREATER (TRAC-TOR MTD)	$500	$63.00	1
64	132040	MOWER, TRAIL TYPE, ROTARY, 9 FT AND GREATER	$50	$7.00	1
65	135050	MOWER, TRACTOR TYPE RIDING, CENTER MOUNT, ROTARY, 30 H.P. AND ABOVE	$50	$7.00	1
66	136010	MOWER, SLOPE, SIDE BOOM, TRACTOR MOUNTED, INC TRACTOR	$635	$80.00	1
67	136020	MOWER, SLOPE, SELF PROPELLED, ROTARY OR FLAIL	$435	$55.00	1
68	140040	PAINT STRIPE MACHINE, 2 COLOR, MULTI-LINE, TRUCK MOUNTED	$1,000	$125.00	3
69	151000	PAVEMENT TEST EQUIPMENT	$350	$44.00	2
70	154000	PAVEMENT PROFILING MACHINE, SELF PROPELLED	$3,000	$375.00	3
71	156010	PAVER, BITUMINOUS, SELF PROPELLED	$2,000	$250.00	3
72	156020	PAVER, BITUMINOUS, TOW TYPE	$235	$30.00	3
73	157000	PAVER, SHOULDER,SELF-PROPELLED	$1,000	$125.00	3
74	160010	PLATFORM LIFT, PERSONNEL, SELF PROPELLED, SCISSORS TYPE	$125	$16.00	1
75	160020	PLATFORM LIFT, PERSONNEL, TRUCK MOUNTED (INCLUDES TRUCK)	$320	$40.00	1
76	162020	PULVERIZER-MIXER, EARTH, SELF PROPELLED	$1,600	$200.00	2
77	165000	REFUELER, TRUCK MOUNTED	$425	$54.00	3
78	170010	ROLLER, FLATWHEEL, SELF PROPELLED 4-6 TON W/PNMTC TRS	$275	$35.00	2
79	170020	ROLLER, FLATWHEEL, SELF PROPELLED 5-8 TON	$300	$38.00	2
80	170030	ROLLER, FLATWHEEL, SELF PROPELLED 8-14 TON	$335	$42.00	2

<table>
<tr><th>Serial No.</th><th>Code</th><th>Code Description</th><th>Daily Rate</th><th>Hourly Rate</th><th>Risk Factor</th></tr>
<tr><td>81</td><td>172000</td><td>ROLLER, GRID, TOW TYPE</td><td>$215</td><td>$27.00</td><td>2</td></tr>
<tr><td>82</td><td>174010</td><td>ROLLER, PNEUMATIC TIRED, SELF PROPELLED</td><td>$900</td><td>$113.00</td><td>2</td></tr>
<tr><td>83</td><td>174020</td><td>ROLLER, PNEUMATIC TIRED, TOW TYPE</td><td>$215</td><td>$27.00</td><td>2</td></tr>
<tr><td>84</td><td>176010</td><td>ROLLER, TAMPING, SELF PROPELLED</td><td>$215</td><td>$27.00</td><td>2</td></tr>
<tr><td>85</td><td>176020</td><td>ROLLER, TAMPING, TOW TYPE</td><td>$50</td><td>$7.00</td><td>2</td></tr>
<tr><td>86</td><td>178010</td><td>ROLLER, VIBRATING, SELF PROPELLED</td><td>$275</td><td>$35.00</td><td>2</td></tr>
<tr><td>87</td><td>178020</td><td>ROLLER, VIBRATING, SELF PROPELLED W/PNEUMATIC TIRES</td><td>$435</td><td>$55.00</td><td>2</td></tr>
<tr><td>88</td><td>179010</td><td>SAW, CONCRETE, 65 H.P. AND ABOVE</td><td>$200</td><td>$25.00</td><td>2</td></tr>
<tr><td>89</td><td>180000</td><td>SCRAPER, ELEVATING, W/INTEGRAL TRACTOR</td><td>$1,500</td><td>$188.00</td><td>3</td></tr>
<tr><td>90</td><td>186000</td><td>SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED</td><td rowspan="2">$100</td><td rowspan="2">$13.00</td><td>2</td></tr>
<tr><td>91</td><td>186010</td><td>SIGN, ELECTRONIC CHANGEABLE, TRAILER MOUNTED, SOLAR PWRED</td><td>2</td></tr>
<tr><td>92</td><td>188000</td><td>SKID TEST TRAILER</td><td>$400</td><td>$50.00</td><td>2</td></tr>
<tr><td>93</td><td>190010</td><td>SNOW PLOW, HIGH SPEED EXPRESS WAY, 10 FT.</td><td>$150</td><td>$19.00</td><td>3</td></tr>
<tr><td>94</td><td>190020</td><td>SNOW PLOW, STRAIGHT MOLDBOARD, 10 FT.</td><td>$150</td><td>$19.00</td><td>3</td></tr>
<tr><td>95</td><td>190030</td><td>SNOW PLOW, ROTARY TYPE, CARRIER MOUNTED</td><td>$1,000</td><td>$125.00</td><td>3</td></tr>
<tr><td>96</td><td>190040</td><td>SNOW BLOWER, FOR MOUNTING ON PNEUMATIC LOADER</td><td>$850</td><td>$107.00</td><td>3</td></tr>
<tr><td>97</td><td>192010</td><td>SPRAYER, HERBICIDE/INSECTICIDE, TRUCK MOUNTED (INC TRK)</td><td>$200</td><td>$25.00</td><td>1</td></tr>
<tr><td>98</td><td>194010</td><td>SPREADER, AGGREGATE, SELF POWERED</td><td>$900</td><td>$113.00</td><td>3</td></tr>
<tr><td>99</td><td>198000</td><td>STORM & DRAIN PIPE CLEANING UNIT, TRUCKMOUNTED</td><td>$2,000</td><td>$250.00</td><td>2</td></tr>
<tr><td>100</td><td>198010</td><td>STORM & DRAIN PIPE CLEANING UNIT, TRAILER MOUNTED</td><td>$350</td><td>$44.00</td><td>2</td></tr>
</table>

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
101	200000	SWEEPER, INDUSTRIAL, SELF PROPELLED	$150	$19.00	1
102	202010	SWEEPER, ROAD, SELF PROPELLED	$250	$32.00	1
103	204020	SWEEPER, STREET, TRUCK MOUNTED	$1,200	$150.00	1
104	204030	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, UP TO 5.9 CY	$800	$100.00	1
105	204040	SWEEPER, STREET, TRUCK MOUNTED, REGENERATIVE AIR, 6 CY & UP	$1,000	$125.00	1
106	210020	TANK, FUEL, TRAILER MOUNTED	$50	$7.00	1
107	212000	TANK, STORAGE, PORTABLE	$25	$4.00	1
108	214000	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, MILEAGE			2
109	214010	TANK, WATER, TRUCK MOUNTED, INCLUDES TRUCK, HOURLY	$275	$35.00	2
110	214020	TANK, WATER, TRAILER MOUNTED			2
111	216040	THERMOPLASTIC STRIPING MACHINE SYSTEM, TRAILER MOUNTED	$250	$32.00	3
112	220010	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) TO 100 HP	$365	$46.00	2
113	220020	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 100-129 HP	$535	$67.00	2
114	220030	TRACTOR, CRAWLER TYPE (W/OR W/O DOZER) 130-179 HP	$725	$91.00	2
115	220040	TRACTOR, CRAWLER TYPE (W/ OR W/O DOZER) 180 H.P. & GREATER	$1,100	$138.00	2
116	230010	TRACTOR, PNEUMATIC TIRED, TO 49 HP (TRACTOR ONLY)	$250	$32.00	1
117	230020	TRACTOR, PNEUMATIC TIRED, 50-64 HP (TRACTOR ONLY)	$250	$32.00	1
118	230030	TRACTOR, PNEUMATIC TIRED, 65 HP & GREATER (TRACTOR ONLY)	$320	$40.00	1
119	240010	TRACTOR, PNEUMATIC TIRED, W/ FRONT END LOADER	$250	$32.00	2
120	240020	TRACTOR, PNEUMATIC TIRED, W/LOADER & BACKHOE, TO 60 HP	$240	$30.00	2

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
121	240030	TRACTOR, PNEUMATIC TIRED, W/LOADER AND BACKHOE, 60 HP & UP	$240	$30.00	2
122	250010	TRAILER, CARGO, ENCLOSED, TAG-ALONG	$120	$15.00	1
123	250020	TRAILER, FIELD LABORATORY OR OFFICE	$300	$38.00	1
124	250030	TRAILER, INSTRUMENTATION, MLS	$450	$57.00	1
125	260010	TRAILER, EQUIPMENT, TILT BED/UTILITY, TO 24,000 LB CAPACITY	$100	$13.00	1
126	260020	TRAILER, EQUIPMENT, TILT BED/UTILITY, 24,000 LB CAP & GREATER	$245	$31.00	1
127	260030	TRAILER, EQUIPMENT, GOOSENECK	$475	$60.00	2
128	270010	TRAILER, MATERIAL, HYDRAULIC DUMP	$230	$29.00	2
129	270020	TRAILER, MATERIAL, TAG END DUMP TYPE			2
130	270030	TRAILER, BULK PRESSURE	$575	$72.00	2
131	280010	TRAILER, TRANSPORT, PLATFORM	$260	$33.00	2
132	280020	TRAILER, TRANSPORT, SIGN			2
133	280030	TRAILER, TRANSPORT, VAN	$135	$17.00	2
134	292000	TRAILER, POLE			2
135	300000	TREE SPADE, TRAILER MOUNTED	$150	$19.00	1
136	302000	TRENCHING MACHINE	$230	$29.00	2
137	302010	TRENCHER, WALK BEHIND	$100	$13.00	2
138	305000	ROCK/CONCRETE CUTTER, CRAWLER MOUNTED	$375	$47.00	2
139	400010	TRUCK, 4-WD UTILITY AND CARRYALL	$140	$18.00	1
140	400020	TRUCK, 4-WD PICKUP, ALL STYLES	$250	$32.00	1

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
141	400030	TRUCK, 2-WD UTILITY VEHICLE, 3961-5000 GVWR	$80	$10.00	1
142	410010	TRUCK, CARRYALL, UP TO 6950 LB GVWR	$140	$18.00	1
143	410020	TRUCK, CARRYALL, 7000 LB GVWR AND GREATER	$160	$20.00	1
144	420010	TRUCK, CARGO OR WINDOW VAN, MINI, UP TO 6200 LB GVWR	$100	$13.00	1
145	420020	TRUCK, CARGO OR WINDOW VAN, FULL-SIZE, 6200 LB GVWR & UP			1
146	420030	TRUCK, STEP OR WALK-IN VAN			1
147	430010	TRUCK, LIGHT DUTY, PICKUP, UP TO 4600 LB GVWR	$175	$22.00	1
148	430020	TRUCK, LIGHT DUTY, PICKUP, 4600 - 6199 LB GVWR			1
149	430030	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 4600-6199 GVWR			1
150	430040	TRUCK, HEAVY DUTY COMPACT, 4320-5600 GVWR	$200	$25.00	1
151	430050	TRUCK, EXTENDED CAB COMPACT, 4245-5034 GVWR			1
152	430070	TRUCK, EXTENDED CAB 1/2 TON, 6000-6799 GVWR			1
153	440010	TRUCK, LIGHT DUTY, PICKUP, 6200-7999 LB GVWR	$215	$27.00	1
154	440020	TRUCK, LIGHT DUTY, OTHER BODY STYLES, 6200-7999 GVWR			1
155	440030	TRUCK, EXTENDED CAB 3/4 TON, 6800-9000 GVWR			1
156	450010	TRUCK, LIGHT DUTY, 8000-8599 GVWR, PICKUP BODY	$280	$35.00	1
157	450020	TRUCK, LIGHT DUTY, 8000-8599 GVWR, OTHER BODY STYLES			1
158	460010	TRUCK, LIGHT DUTY, 8600-14999 GVWR, PICKUP BODY			1
159	460020	TRUCK, LIGHT DUTY, 8600-14999 GVWR, OTHER BODY STYLES	$310	$39.00	1
160	470020	TRUCK, LIGHT DUTY, CR CAB, 7901-8599 GVWR, OTHER BODY STYLES			1

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
161	470030	TRUCK, LIGHT DUTY, CR CAB, 8600-14999 GVWR, OTHER BODY STYLES			1
162	480010	TRUCK, PLTFM, PLTFM DUMP, STAKE, 8600-14999 GVWR			1
163	480060	TRUCK,PLATFORM, PLATFORM DUMP, STAKE, 8600 TO 14,999 GVWR,HRL RATE			1
164	490010	TRUCK, LIGHT/MEDIUM, 14,500 TO 18,999 GVWR	$310	$39.00	1
165	500010	TRUCK, ALL BODY STYLES, 15,000-18,900 GVWR			1
166	500020	TRUCK, CREW CAB, ALL BODY STYLES, 15000 TO 18900 GVWR			1
167	510010	TRUCK, ALL BODY STYLES, 19,000-20,900 GVWR			1
168	520010	TRUCK, ALL BODY STYLES EXC CONV DUMP, 21000-25400 GVWR			1
169	520020	TRUCK, CONVENTIONAL DUMP, 21000-25400 GVWR	$500	$63.00	2
170	520030	TRUCK, EJECTION TYPE MATERIAL BODY, 21000-25400 GVWR			2
171	520040	TRUCK, CREW CAB, ALL BODY STYLES, 21000 TO 25400 GVWR	$350	$44.00	1
172	530010	TRUCK, ALL BODY STYLES, EXC CONV DUMP/WRKR 25500-28900			1
173	530020	TRUCK, CONVENTIONAL DUMP, 25500-28900 GVWR	$650	$82.00	2
174	530030	TRUCK, EJECTION TYPE MATERIAL BODY, 25500-38900			2
175	530040	TRUCK, WRECKER	$350	$44.00	1
176	530050	TRUCK, CREW CAB, ALL BODY STYLES, 25500 TO 28900 GVWR	$400	$50.00	1
177	530060	TRUCK, 25500 TO 28900 GVWR, ALL STYLES, HOURLY RATE			1
178	540010	TRUCK, DUMP, SINGLE REAR AXLE,29000-42900 GVWR	$650	$82.00	2
179	540020	TRUCK, DUMP, TANDEM REAR AXLE, 43000 GVWR AND GREATER	$895	$112.00	2
180	550010	TRUCK, ALL STYLES EXC DUMP, SINGLE REAR AXLE 29000-38900	$500	$63.00	2

Serial No.	Code	Code Description	Daily Rate	Hourly Rate	Risk Factor
181	550020	TRUCK, ALL STYLES EXC DUMP, TANDEM REAR AXLE 39000 +	$650	$82.00	2
182	550030	TRUCK, ALL STYLES EXCEPT DUMP, SINGLE REAR AXLE, 29000-38900 GVWR HRLY	$650	$82.00	1
183	550040	TRUCK, ALL STYLES EXCEPT DUMP, TANDEM REAR AXLE, 39000 GVWR AND UP	$895	$112.00	1
184	600010	TRUCK TRACTOR, SINGLE REAR AXLE, UP TO 60000 GCWR	$155	$20.00	1
185	600020	TRUCK TRACTOR, SINGLE REAR AXLE, 60000 GCWR & GREATER			1
186	600030	TRUCK TRACTOR, TANDEM REAR AXLE, ALL GCWR	$170	$22.00	1
187	710010	VEHICLE, ALL TERRAIN	$50	$7.00	1
188	710020	VEHICLE, PERSONNEL, 3 WHEEL, ENGINE DRIVEN			1
189	720000	VIDEO, COMMUNICATIONS, TRAILER MTD, WITH OR W/O MESSAGE BOARD (ITS)	$1,000	$125.00	3
190	901010	CORE DRILL, SPECIMEN, SKID MOUNTED	$100	$13.00	2
191	913000	PAINT SPRAY OUTFIT, TRAILER MOUNTED	$100	$13.00	2
192	916010	PUMP AND ENGINE, PORTABLE, 3"	$50	$7.00	2
193	917000	PUMP, PTO DRIVEN, 4"	$75	$10.00	2
194	921000	SNOW PLOW, V-TYPE	$150	$19.00	3
195	927000	TRAILER, EQUIPMENT, 1-1/2 THRU 3 TON	$75	$10.00	1
196	928000	TRAFFIC ALERTING & CHANNELING DEVICE, ARROW, TRAILER MOUNTED	$75	$10.00	3
197	928010	TRAFFIC ALERTING & CHANNELING DEVICE, ARROW, TRLR MTD, SOLAR	$50	$7.00	3

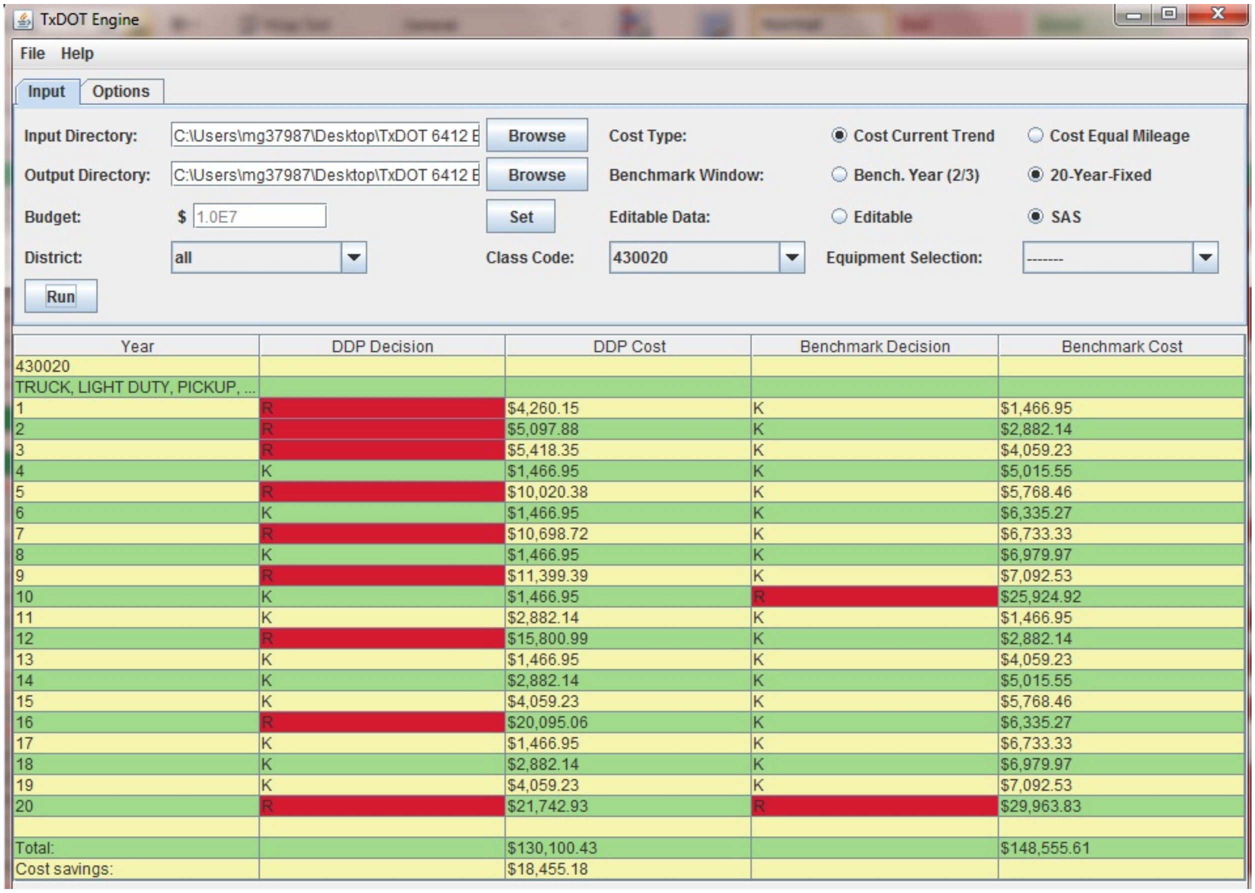
Due to the fact that some vehicles and equipment units have large amounts of down time recorded in the database, these rates can have a substantial impact on estimates of O&M costs. The detailed assessment of these O&M costs was undertaken as part of evaluating preliminary optimization results.

Chapter A.4. Estimating O&M Costs

In addition to establishing a practical rate for down time hours for each individual classcode, the overall O&M costs were evaluated. To derive the O&M costs for each vehicle or equipment unit, nine data fields provided in the TxDOT TERM database are summed. These fields include all costs coded as repair expenses, gas, diesel, oil, other fuel, hydraulic and other fluids, down time, parts, and labor. Several issues were identified from a thorough review of the resulting numbers and subsequent optimization results. It was determined that a software algorithm be developed for SAS to evaluate the O&M costs for each classcode and establish the best possible methodology for forecasting these costs for the ERO horizon. The following sections identify a number of issues discovered from the in-depth review of the ERO results and O&M cost data, the solutions identified for improving the cost forecasts, and the algorithm developed for implementing the solution strategies into the software.

A.4.1 Review of Preliminary O&M Cost Forecasts

Since the optimization's keep versus replace decision is based on a comparison of the purchase cost less the salvage value versus the O&M costs, a thorough evaluation of the O&M costs, as with the purchase cost forecasts, was required. It was determined from preliminary optimization results that many light duty vehicles were being recommended for replacement within the first three years of purchase. This is clearly a counterintuitive result. Figure A.4.1 illustrates an output from the ERO software with this type of result for classcode 430020 (light-duty pickup truck).



Year	DDP Decision	DDP Cost	Benchmark Decision	Benchmark Cost
430020				
TRUCK, LIGHT DUTY, PICKUP, ...				
1	R	$4,260.15	K	$1,466.95
2	R	$5,097.88	K	$2,882.14
3	R	$5,418.35	K	$4,059.23
4	K	$1,466.95	K	$5,015.55
5	R	$10,020.38	K	$5,768.46
6	K	$1,466.95	K	$6,335.27
7	R	$10,698.72	K	$6,733.33
8	K	$1,466.95	K	$6,979.97
9	R	$11,399.39	K	$7,092.53
10	K	$1,466.95	R	$25,924.92
11	K	$2,882.14	K	$1,466.95
12	R	$15,800.99	K	$2,882.14
13	K	$1,466.95	K	$4,059.23
14	K	$2,882.14	K	$5,015.55
15	K	$4,059.23	K	$5,768.46
16	R	$20,095.06	K	$6,335.27
17	K	$1,466.95	K	$6,733.33
18	K	$2,882.14	K	$6,979.97
19	K	$4,059.23	K	$7,092.53
20	R	$21,742.93	R	$29,963.83
Total:		$130,100.43		$148,555.61
Cost savings:		$18,455.18		

Figure A.4.1 Software Output Display with Early Replacement Recommendations for Classcode 430020

Upon investigation, it was found that many vehicles had high, early O&M costs. An in-depth review of the recorded O&M costs for these classcodes, as well as many others, revealed that these costs were noticeably high, particularly in the first two years of deployment. This included a number of the individual O&M cost fields, including repair expenses and down time. With new down time rates established, including those higher than initially coded, in order to better represent the cost of losing certain mission critical pieces of equipment, this problem was even more perceptible.

It was concluded that some adjustments to the data would be required to properly generate applicable forecasting models for O&M costs. A discussion with TxDOT fleet management staff (progress meeting on February 1, 2012) revealed that the early repair costs and associated down time, particularly for the first two years of operation, were likely associated with make-ready costs for vehicles and equipment and were thus, coded inadequately for the ERO process. It was decided that these costs are not the true O&M costs intended to be used as part of the decision algorithm. Therefore, a logical adjustment would need to be made to the raw data to properly forecast true O&M costs.

A.4.1.1 Adjustments to O&M Costs (First Two Years of Operation)

As part of the overall O&M cost totals, it was determined that the coded values for repair expenses, as well as down time, labor, and parts costs would need to be adjusted. Those expenses associated exclusively with operations, including gas, diesel, oil, other fuel, and hydraulic and other fluids would remain as originally coded. In addition, any adjustment would be made for the first two years alone, as any repair expenses beyond that point could be more realistically considered to be true maintenance.

The adjustments included moving all repair expenses entered for the first two years of operation from that field to the net adjusted capital field. That way, make-ready costs, including upgrades to vehicles, could be captured more appropriately. Furthermore, down time, labor, and parts costs were adjusted to one-tenth of their original value. It was determined that some costs coded in these fields may adequately account for oil changes and general maintenance and should remain non-zero; however, these costs would be minimal compared to some of the values observed in the data. Down time entries were found to exceed 100 hours in some cases as reported in the first year of operation and were believed to be associated with vehicles waiting for make-ready modifications. These adjustments resulted in significantly lower O&M costs in the first two years for all equipment classcodes.

To test the impact of the adjustments, seven light duty and seven heavy duty vehicles were selected for comprehensive evaluation. A comparison was made of the unadjusted O&M costs versus the adjusted O&M costs to determine how the modifications might impact the trends in annual O&M cost forecasting and, ultimately, the ERO decision process. The average annual, unadjusted O&M costs for the seven light duty classcodes chosen are shown in Figure A.4.2.

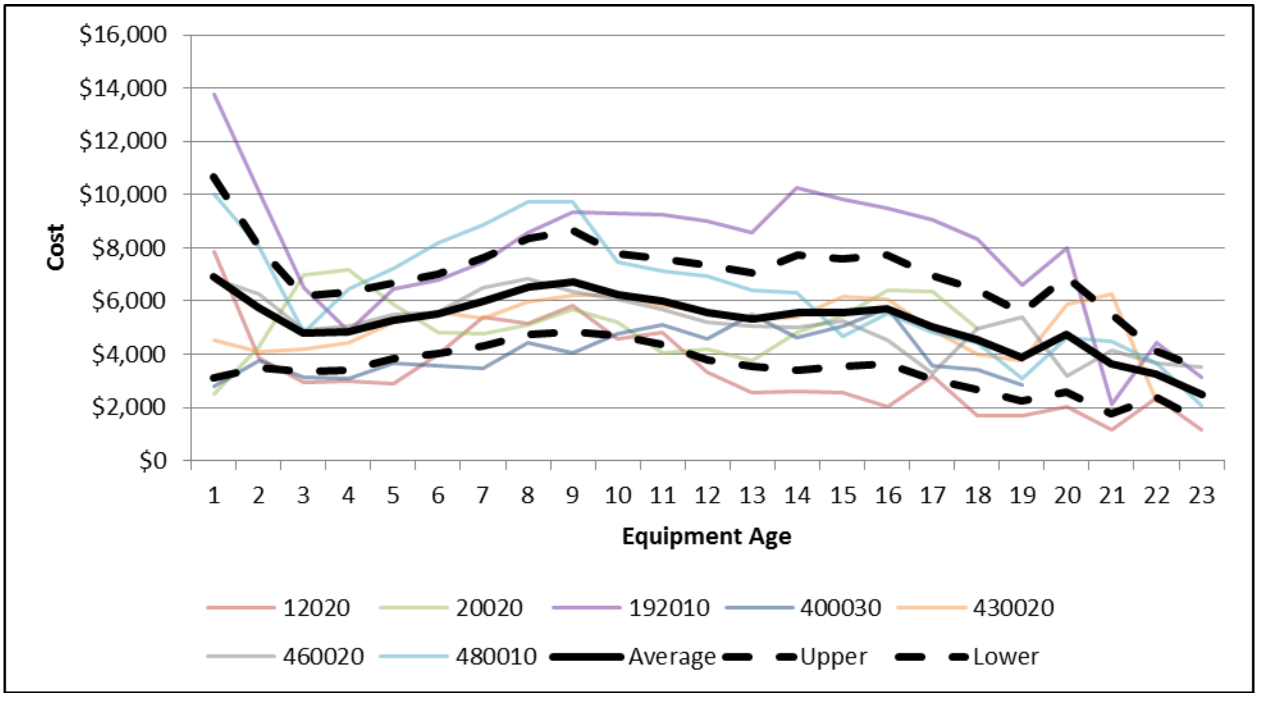


Figure A.4.2 Original Average O&M Costs for Select Light Duty Vehicles

The figure illustrates the trends for the selected light duty vehicles in terms of average O&M costs using the numbers as originally coded and analyzed (i.e., no adjustments to the first two years of operation and a $25 per hour down time rate). The figure highlights the issue with high early O&M costs. It also sheds light on another issue with the data. It illustrates how the O&M costs reach a peak at about the 10-year old mark and then taper off toward the latter years of the equipment's life cycle. The fact that O&M costs are decreasing with age after a point is not intuitive and is not consistent with trends identified in the literature, particularly with the US Army fleet (Pint et al., 2008). This trend suggests that as vehicles have gotten older, there has been a tendency for them to be used less by TxDOT personnel and they have been, therefore, incurring lower O&M costs. This trend is expected to change as future data becomes available due to TxDOT's recent right-sizing efforts. It is likely that the impact of this process has not permeated through the data. Nonetheless, this trend was identified as a possible complication for forecasting O&M costs.

For the above classcodes the graph indicates lower utilization of these vehicle types after about 10 years of age. The upper and lower bounds, identified in the legend, correspond to the 95th percentile limits of the data. Figure A.4.3 shows the trend for the same light duty vehicles in terms of average O&M costs using the adjusted values for the first two years. This includes the removal of repair expenses and 90-percent of the original down time, parts, and labor costs, as well as a down time cost adjusted to coincide with the rental rate for each individual classcode. The figure illustrates the change in O&M costs in the early years, but understandably, does not correct for the existing phenomenon with the lower cost/utilization as equipment ages.

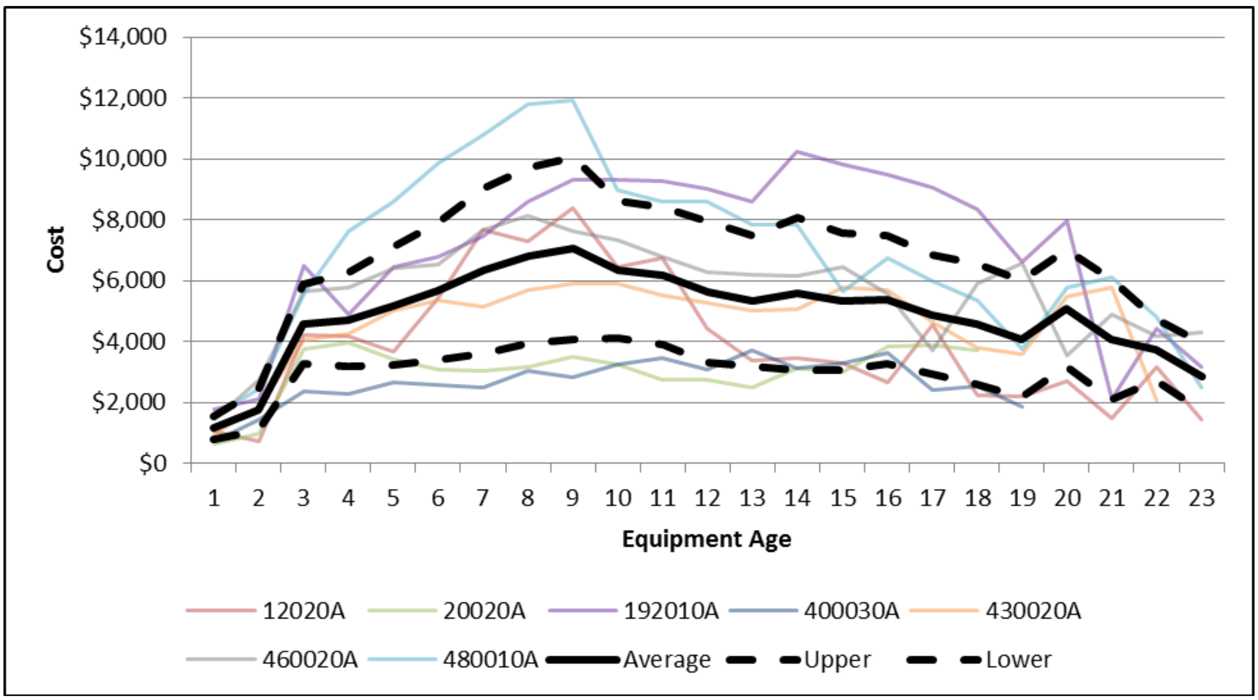


Figure A.4.3 Adjusted Average O&M Costs for Select Light Duty Vehicles

Likewise, the analysis of select heavy duty vehicles revealed similar trends. Figure A.4.4, below, illustrates the trend for seven selected heavy duty vehicles in terms of average O&M costs using the numbers as originally recorded. The graph again highlights the issue with high early O&M costs, although not quite as pronounced in the first year as with the light duty classcodes. It further illustrates how the trend peaks and, in this case, tapers off after about the 15-year mark. This trend is indicative of lower utilization of these vehicle types after about 15 years of age.

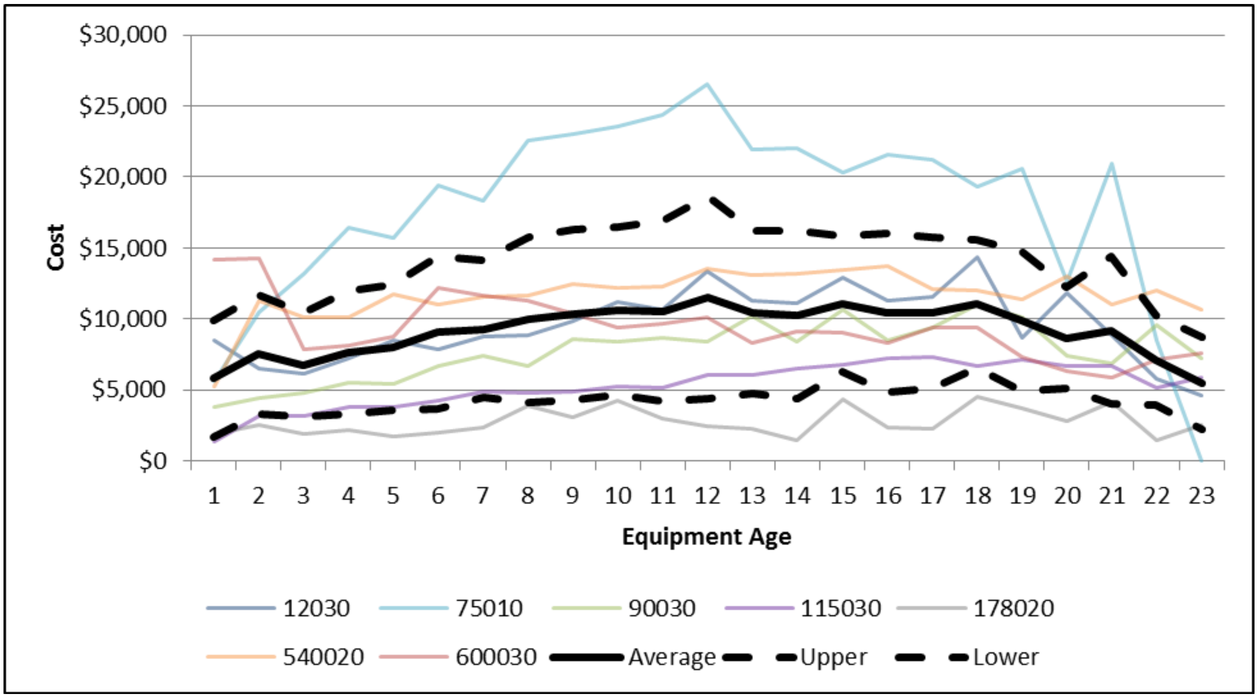


Figure A.4.4 Original Average O&M Costs for Select Heavy Duty Vehicles

As with the light duty vehicles, the modification to the first two years of data yields a significant change in the early O&M cost numbers. Figure A.4.5 shows the trends for the same heavy duty vehicles in terms of average O&M costs using the adjusted values for the first two years, along with the updated down time rate. The sharp increase in year three can be clearly identified as the unadjusted O&M costs are significantly higher for the heavy duty vehicles. The sharp increase at this point is also contributed by the higher down time rate for heavy duty vehicles and more expensive repair costs, no longer constrained after year two.

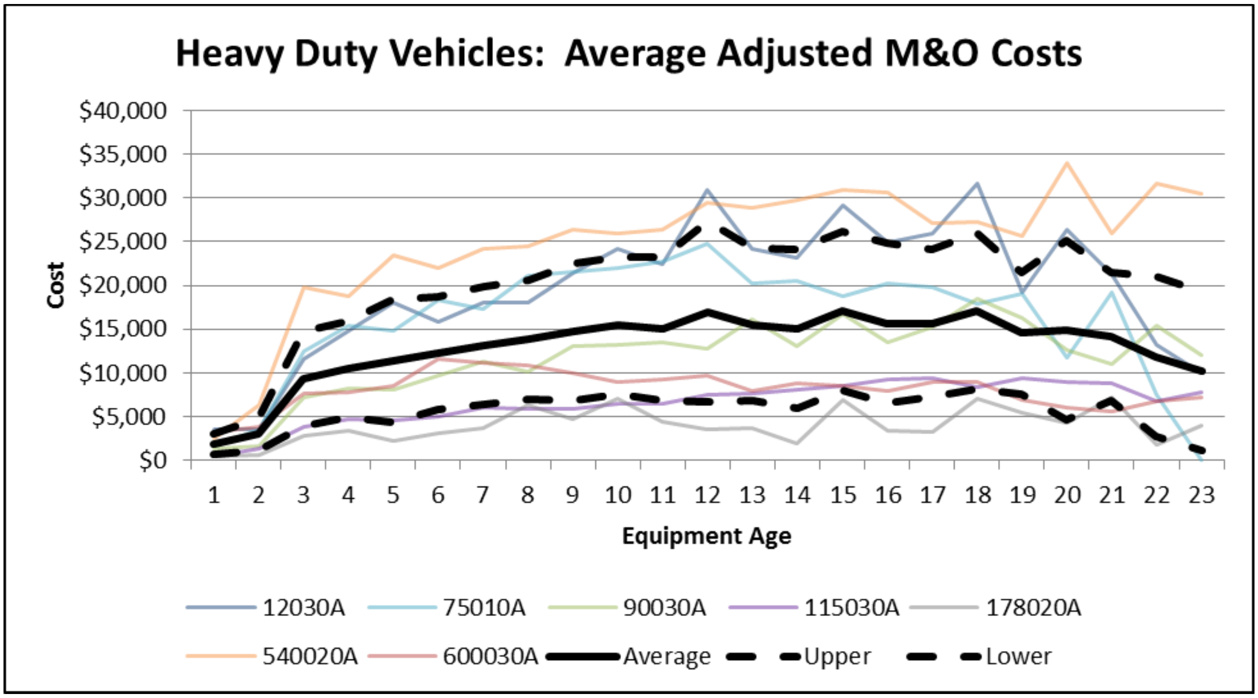


Figure A.4.5 Adjusted Average O&M Costs for Select Heavy Duty Vehicles

Per approval from TxDOT fleet management personnel, the described modifications to the O&M costs, including down time rate adjustments, were incorporated into the software and the cost forecasts were updated accordingly. After implementing these changes, the results of the ERO process were reviewed for all of the classcodes. As part of this evaluation, several issues were evident from the software's replacement recommendations. Therefore, an in-depth review of the O&M cost forecasts was subsequently performed.

A.4.1.2 Additional Issues with O&M Cost Forecasts and Solutions Identified

The original strategy for forecasting the O&M costs developed for project 0-6412 depended on the use of SAS, as initiated by the graphical user interface (GUI), to create statistical models based on available historical data. This involved the creation of multiple linear and nonlinear mathematical models to forecast equipment O&M costs for two different strategies: cost current trend and cost equal mileage.

For the cost current trend model, the historical data for annual O&M costs are averaged over all vehicles of a certain age within a classcode and modeled versus the independent variable, equipment age. The resulting model is used to forecast O&M costs for the 20-year horizon. The cost equal mileage strategy involves taking the annual O&M cost total and dividing it by the unit of utilization, miles or hours, for each vehicle. This O&M cost rate is then averaged for all vehicles of a certain age. Once averaged, a statistical model is generated for the average cost rate versus equipment age. In addition, the utilization values are averaged over all vehicles in a given classcode for the most recent year of operation recorded in the database. The average O&M cost rate generated by the model is then multiplied by the average utilization value to provide the forecast for each year in the horizon based on the equipment's age. For both of the O&M cost forecasting strategies, the SAS macro source codes were developed to generate the following five different types of models: 1) Linear Model; 2) Polynomial Model; 3) Logarithm Model; 4) Exponential Model; and 5) Power Model.

The SAS macro also has the capability of running through all of the linear and nonlinear models and automatically identifying and selecting the best-fit model, per the highest R-squared value, for forecasting the O&M costs (based on equipment age) for any chosen classcode. The objective was to use SAS to create and select the best-fit model for the data and incorporate that model for forecasting O&M costs into the optimization engine. For more information about the development of these models and the selection process, see Fan et al. (2011a, 2011b).

Through an in-depth evaluation of the software results, it was discovered that the O&M cost forecasts for a number of the classcodes was unduly influencing the keep/replace decisions for the optimized solution. Further investigation revealed that the software was selecting best-fit models that, in some cases, yielded negative O&M costs for future years. The evaluation of the quality of the fit (R-square value) for the model options led to the software program choosing non-linear models for nearly all of the equipment classcodes. Due to the distribution of data for some of these equipment types, as a result of lower utilization as vehicles age, this resulted in a curvilinear model with a negative slope generated over the latter years of the lives of the equipment units, as illustrated below in Figure A.4.6.

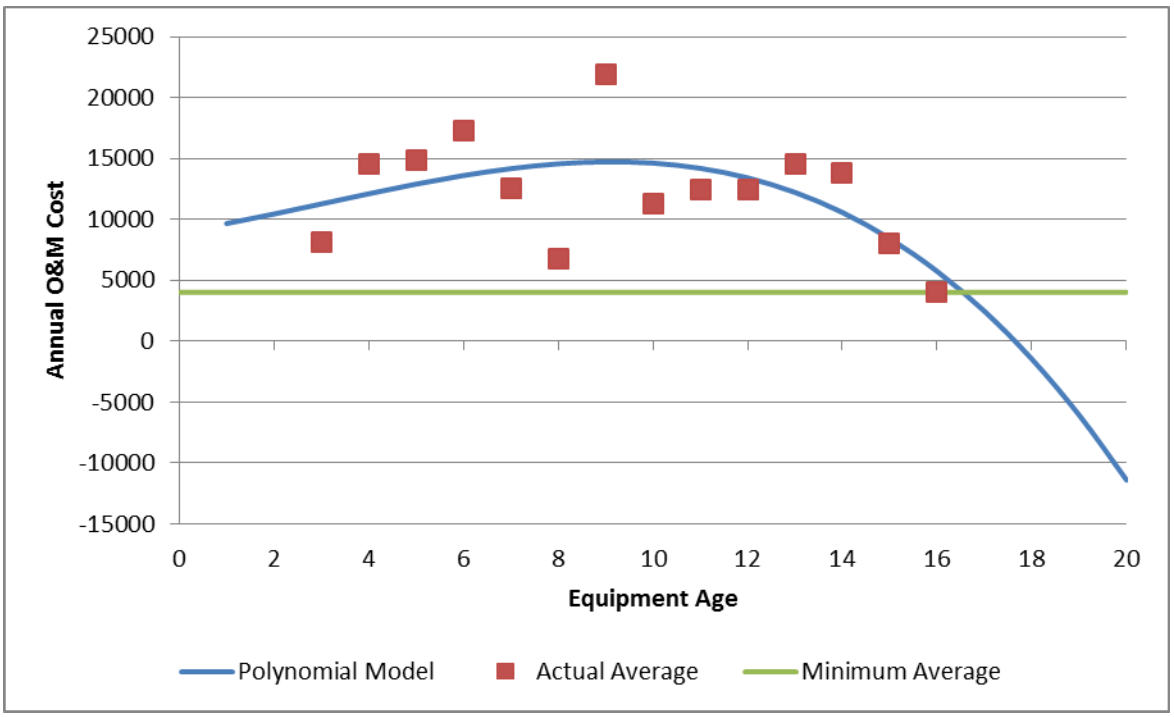


Figure A.4.6 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 400020 (Light Duty Truck, 4-WD Pickup)

Note that Figure A.4.6 shows the nonlinear model yielding a reasonable fit for the data; however, the slope of the model is negative after about year 10, an issue identified earlier, and would subsequently result in negative O&M costs as equipment in this classcode ages beyond 17 years. Therefore, the statistical models like this one result in lower projected O&M costs as vehicles age, and the tendency of the software to not recommend equipment replacement until the end of the horizon (20 years). It was determined that this would have an adverse impact on the ability of the optimization engine to appropriately generate recommendations for replacing equipment, as the decreasing trend as vehicles age is not consistent with expectations. However, it is based on the data available and a countermeasure has been developed to account for this issue.

The problem with lower utilization may be corrected in the future as new data is implemented, since the fleet has been right-sized. Therefore, making changes to the models themselves was not a recommended solution for this issue. Instead, it was determined that a minimum, annual O&M cost value be established for the forecasts based on the available data. It was determined that the model process should be completed and any negative forecasted value be replaced with the minimum value. That value has been determined to be the minimum, annual average O&M cost found in the data across the available equipment ages. This value is illustrated in Figure 4.6 as the "Minimum Average". Note that in this particular case, no O&M cost data exists for vehicles older than 16 years of age, so the minimum for equipment aged 17 to 20 years, must come from an earlier value (i.e., age 16).

Several additional strategies were also discussed, and presented to TxDOT personnel (progress meeting August 16, 2012), including the use of a percentile value (e.g., 10th percentile O&M cost) as the minimum or an experience-based value determined by fleet management personnel due to familiarity with typical O&M costs incurred for keeping equipment operational. Nonetheless, it was determined that using the minimum average calculated by the software, per the data entered and updated each year, be utilized. It was further determined that the minimum values calculated by the software be provided to TxDOT for review and approval. It was also recommended that in these instances, a warning message, or some similar indication, be provided by the ERO software to alert the user that an issue with negative forecasted values was detected upon running the optimization, and that the software was proceeding with the minimum value calculated for that classcode.

Establishing a minimum value for O&M cost forecasts has been found to solve another, similar issue found in the data. It was determined that some of the forecasting models were beginning with negative values due to the lower adjusted O&M costs established for the first two years of operation. Figure A.4.7 illustrates this type of trend as identified for classcode 90040.

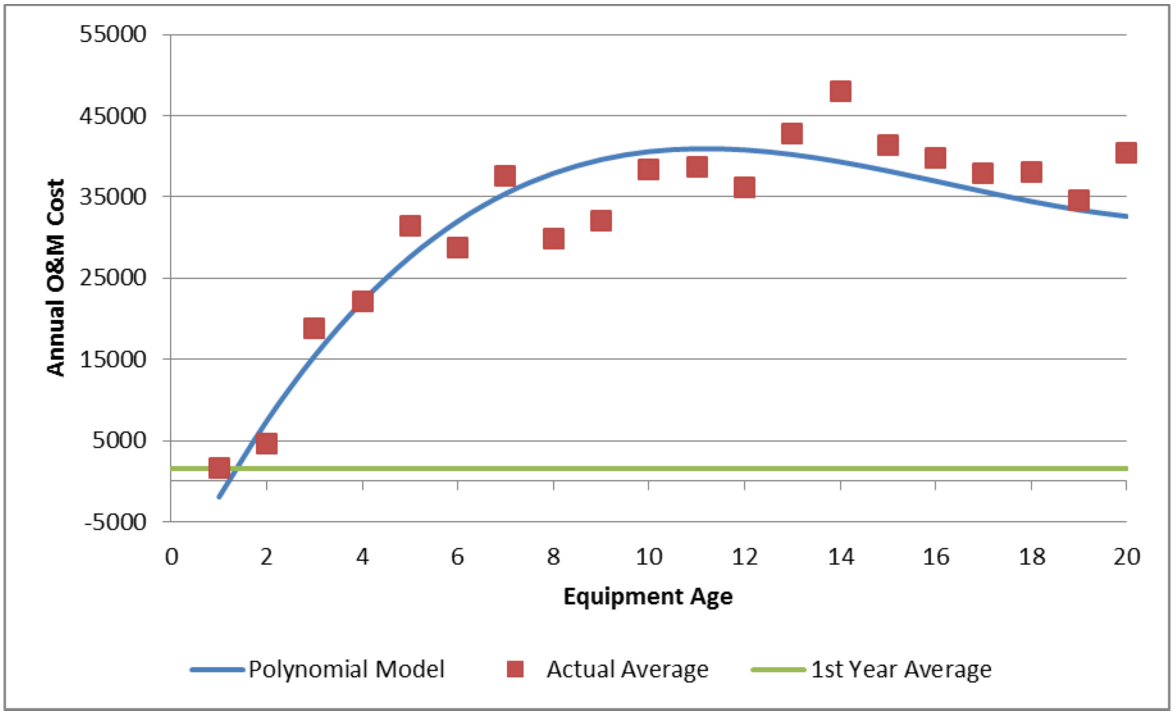


Figure A.4.7 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 90040 (Grader, Motor, Class IV)

While Figure A.4.7 shows a decreasing trend in O&M costs as vehicles age past about 12 years for this classcode, the problem with negative forecasted values appears at the beginning of the life-cycle. Again, a minimum O&M cost value could be used to solve this issue, but in this case, data exists for the year where the model dips below zero. Therefore, the data for that year could be used to establish the minimum. As such, the strategy for calculating a minimum was modified. First, the software is tasked with finding the average O&M cost from the data for the age value where a negative cost has been forecasted, as shown in Figure A.4.7, and to use it if one exists. If none exists, the software is to instead use the minimum average O&M cost calculated from the remaining years available in the data, as mentioned above and illustrated in Figure A.4.6. This two-part strategy was implemented to solve the issue with negative forecasted O&M costs.

Another issue was identified in the review of the TERM data. The method for establishing the cost equal mileage forecast, as identified above, involves the calculation of an O&M cost rate for each vehicle based on the utilization. However, if the data indicated that no O&M costs were incurred, or no utilization was recorded, then this rate is effectively zero. Therefore, these entries yield no measure of O&M cost for aiding in the creation of the forecasting models for this strategy. It was determined that each equipment unit in the fleet is at least inspected annually and thus, acquires a minimal maintenance cost. As such, a minimum O&M cost rate will again be established for each of these classcodes based on the existing data (i.e., the minimum O&M cost rate for a vehicle of the same age) and assigned to any vehicles with an otherwise zeroed out O&M cost rate. These values will be established using the SAS code and implemented in the development of the O&M cost forecasting models for the cost equal mileage method.

Another issue identified with the creation of the O&M cost forecasts, was that the statistical model fits for the chosen models were not always good. The model selection methodology is based on the model with the highest R-squared value being chosen for the established forecast. However, this does not guarantee that a model with a high-quality fit will be chosen. For example, in Figure A.4.7, the polynomial model chosen as the best fit has an R-squared value of 0.33. As such, in a similar manner to the model selection process for the purchase cost forecast, a threshold R-squared value was chosen as a check against the quality of the fit. The value chosen was 0.5, and if no statistical model can be fit to the data with a higher quality than that threshold, then a default option is to be utilized.

The default option for forecasting the O&M cost is to use the average O&M cost for each equipment age value based on the historical data available for an individual classcode. The purpose of this strategy is to provide a fail-safe to ensure that historical data is utilized in the forecast of O&M costs, even if a high-quality model cannot be generated, and only relatively high-quality models be used for forecasting O&M costs. Regardless of the forecasting strategy implemented, TxDOT personnel requested that the GUI provide a warning message to the user when the statistical models fail to generate a model exceeding the R-squared threshold, and regardless of the result, the output Excel file for the O&M cost forecast provide the highest R-squared value achieved (per meeting on August 16, 2012). The established threshold will also prevent issues found with some power and exponential models. When these types of models are chosen as having the best fit for the existing data, they often have the tendency to forecast some counterintuitive results, particularly in the tail ends of the model.

It was found that when exponential and power models are chosen as the best fit for forecasting O&M costs, it is often due to outliers in the data. For some classcodes, only a couple of vehicles (sometimes only one) will be found in the database for a particular age value. This happens most often for vehicles over 15 years of age. If a relatively small sample is available for a specific age, really expensive O&M costs for even one vehicle can have a substantial impact on the average, and thus, unduly influence the statistical model chosen to fit the overall data. An example of where this occurs is shown in Figure A.4.8.

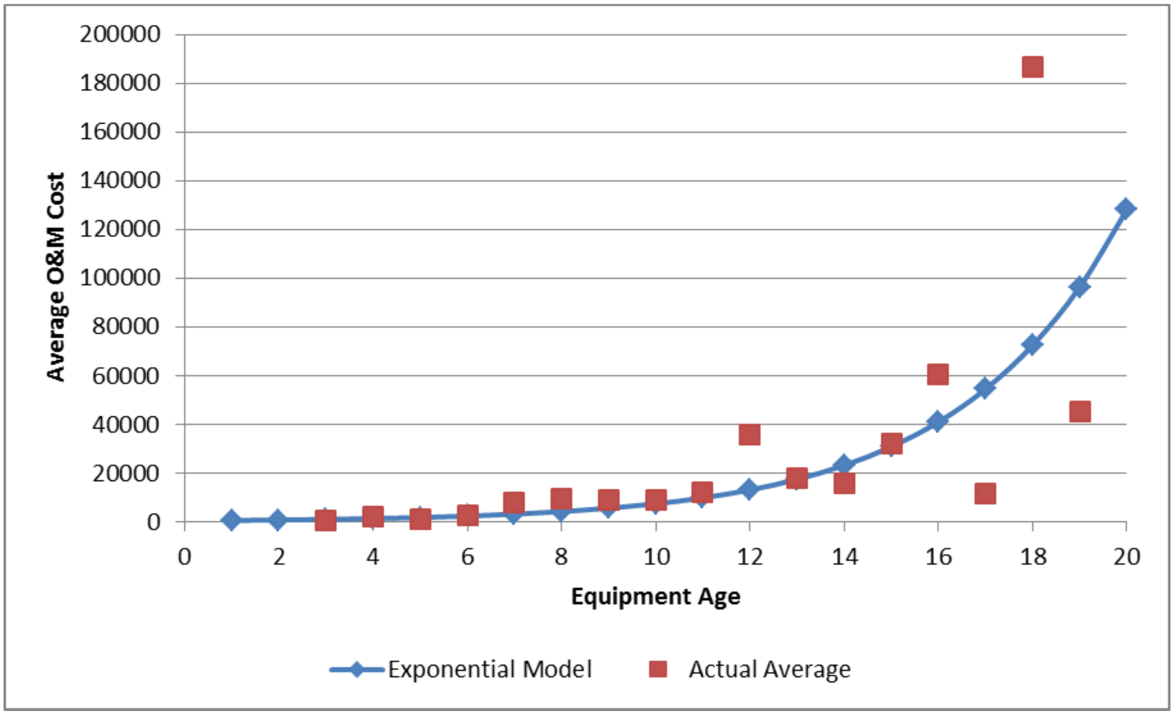


Figure A.4.8 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 520020 (Truck, Conventional Dump)

As can be seen in Figure A.4.8, the average O&M cost for a vehicle aged 18 years old is noticeably higher than 17 or 19. This is due to the extremely high O&M cost recorded for a single vehicle in this category. It should be noted that this model was created for the cost equal mileage methodology. Therefore, an O&M cost rate was calculated and multiplied by the average utilization for all vehicles for this classcode from the most recent year. Since this vehicle is old, the actual utilization was far lower than this average, but the methodology based on equal utilization inflates the forecasted O&M cost. As such, the statistical model chosen was an exponential model with an increasing O&M cost with equipment age that spikes near the end of the horizon. This forecast yields substantially high O&M costs for equipment beyond 17 years of age. It was determined that removal of this, and other similar outliers, might be extremely helpful in the model generation process.

These outliers are removed using an outlier removal process similar to that implemented into the SAS code for the purchase cost forecasts. In addition to the SAS macro based data cleaning process, this outlier removal procedure will be initiated as part of the algorithm to eliminate major outliers from the data before the statistical models are created by the software. To see more information about the SAS macro based data cleaning process involving the first outlier treatment, see Fan et al. (2011a). In the second round of the outlier removal process, specifically for average O&M cost values, upper and lower thresholds are created for a range of acceptable values. Those thresholds are calculated based on the lower and upper quartiles (Q_1 and Q_3) and the subsequent interquartile range ($IQR = Q_3 - Q_1$) as follows:

$$F_1\ (lower\ threshold) = Q_1 - [2 * 1.5 * (Q_3 - Q_1)]$$
$$F_3\ (upper\ threshold) = Q_3 + [2 * 1.5 * (Q_3 - Q_1)]$$

As such, average O&M cost values falling outside the above thresholds are eliminated from consideration for the creation of the statistical models. It was also requested by TxDOT personnel that a warning message appears in the GUI identifying for the user when outliers have been removed (meeting on August 16, 2012). The review process also determined that another issue exists for classcodes with small sample sizes.

In the process of evaluating the ERO software results for each classcode, it was found that the cost estimations were unavailable (i.e., zeroed out) for the entire 20-year horizon for approximately 10 classcodes. Further investigation of the issue revealed that this phenomenon involves classcodes where only one year of purchase cost information is available in the TERM database. If only one year of purchase cost information is available, a forecast cannot be generated; therefore, the optimization process is invalidated. An update to the SAS code was implemented to solve this problem.

The additional outliers will be removed from the O&M cost data and the minimum O&M cost values will be calculated for each classcode by the software. Furthermore, the statistical models generated will be evaluated against a minimum R-squared value. This threshold has been established for choosing between a statistical model and the historical average for forecasting O&M costs. With these, along with a few additional modifications to the SAS code to ensure a forecast is generated for all classcodes, regardless of sample size, the details for a software algorithm have been finalized.

A.4.1.3 Implementing a Software Algorithm

The process of implementing a software algorithm to resolve the issues with the O&M cost forecasts has been initiated. The identified software algorithm, using SAS macro codes, is provided in Figure A.4.9.

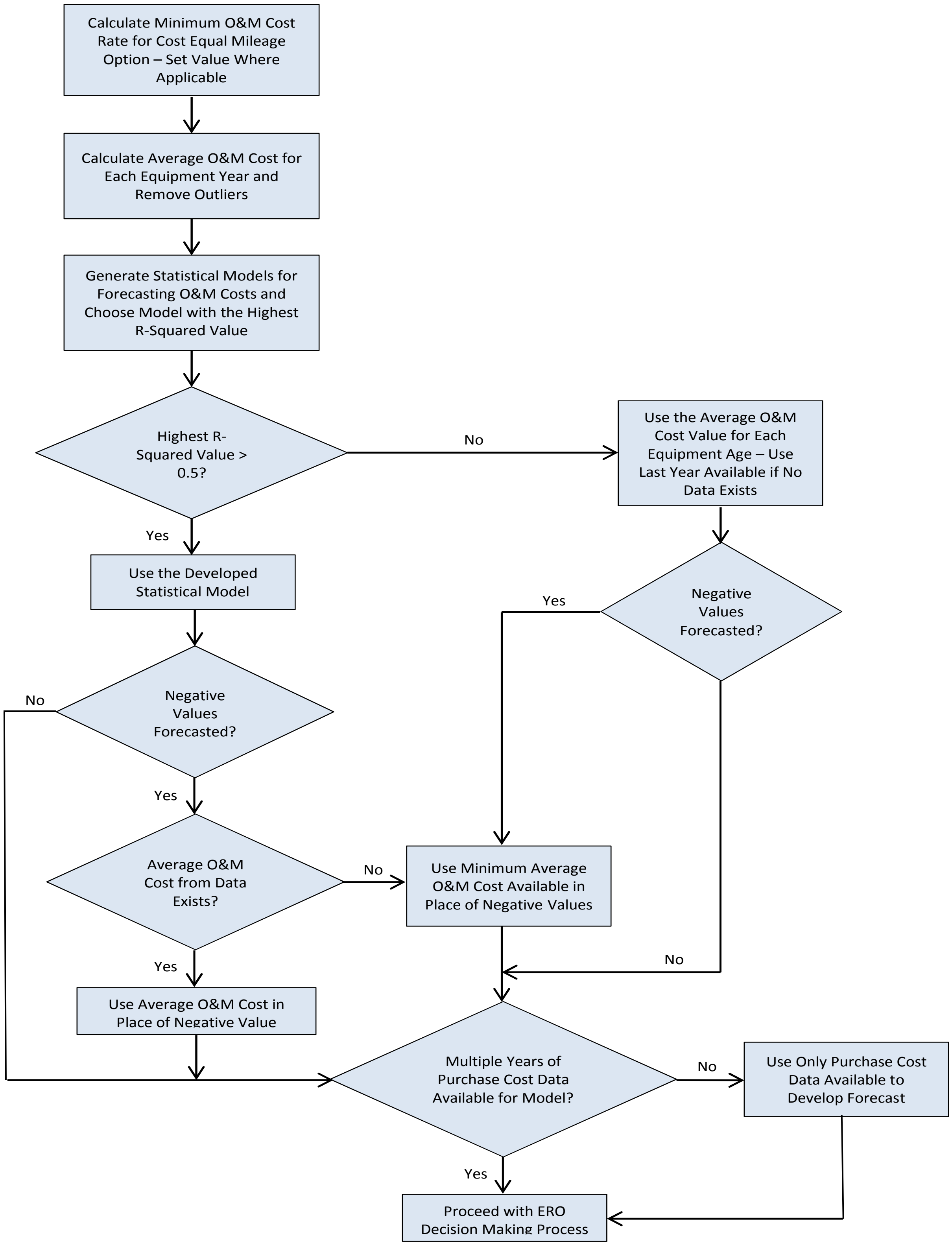


Figure A.4.9 Flow Chart of the O&M Cost Forecasting Algorithm Software Implementation

As shown in Figure A.4.9, the algorithm first calculates the appropriate average annual O&M values and removes any outliers across all equipment ages using the IQR method. Then, it creates the statistical models and chooses the one with the highest R-squared value. The software subsequently checks whether or not the R-squared value is great than 0.5. If the model passes the threshold check, the software then determines if any forecasted O&M costs are negative. If it fails the threshold check on the R-squared value, the forecast uses the existing average O&M values based on equipment age. If any forecasted values are negative from either method, the software uses the described process for establishing and utilizing a minimum annual O&M value. With the appropriate O&M forecast in place, the software checks for the availability of purchase cost data for creating a purchase cost model. If such data exists, a purchase cost model is created and the ERO decision is evaluated based on the appropriate forecasts. If a model cannot be generated, the available purchase cost information is utilized as the forecast, and the ERO process continues.

A.4.1.4 Reviewing the Results

In order to review the level of success achieved from applying the algorithm, the forecasted O&M costs for all of classcodes was evaluated. The O&M cost forecasts were checked for negative values, and the statistical models were evaluated for quality of fit. Average O&M cost values were also reviewed to confirm that all outliers had been removed. Subsequent ERO results were evaluated in both SAS environments and the GUI. It is intended that the software algorithm be developed and implemented such that all classcodes will generate appropriate forecasts and results, based on the best available use of the historical TERM data, regardless of sample size or other characteristics of the data. The comprehensive testing of all classcodes indicated satisfactory and quality down time cost, O&M cost, and mileage forecasts. A significant amount of money has been estimated to be saved annually by TxDOT using the developed ERO software.

A.4.2 Summary

The purpose of this task was to estimate down time costs unique to each equipment classcode in the TxDOT TERM database and investigate operations and maintenance (O&M) costs coupled with TxDOT's recent fleet rightsizing efforts. The original strategy for estimating down time was to use one universal rate for all classcodes. However, this estimate was limited, as vehicles from different classcodes are likely have distinctive non-availability costs. Therefore, a unique rate was established for each individual classcode based on techniques found from a review of relevant literature. Since down time is part of the overall O&M costs for each equipment unit, its proper estimation was a critical component in establishing forecasts for O&M costs.

Based on the TxDOT TERM data, the research team developed five different types of models (including Linear/Polynomial/Logarithm/Exponential/Power models) in TERM2 through project 0-6412 to forecast O&M costs using equipment age as the independent variable. Upon implementation of the original strategy, some forecasted O&M costs were found to be much higher or lower than expected, and in some extreme cases, negative. Early replacements were being recommended in the ERO results, and other issues were noticeable from a full review of the forecasts for each classcode.

One of the issues identified included high, early O&M costs across many of the classcodes. An appropriate strategy was developed and approved for modifying the first two years of cost data prior to being utilized for generating statistical models. Another issue found was the forecast of negative O&M costs based on the statistical models. It was determined that replacing these negative forecasts with minimum, annual O&M cost values, calculated from the historical TERM data, would be appropriate for resolving this problem. Furthermore, it was determined that establishing minimum O&M cost rates would be necessary for populating missing entries (due to zero O&M costs or utilization recorded for specific vehicles) for the cost equal mileage option.

In addition, as part of the statistical model generating process, establishing a minimum threshold value for R-squared to control for the chosen model's goodness-of-fit, along with a second outlier removal process, were necessary for improving the accuracy of forecasted results. Lastly, it was found that minimal sample sizes, including that for purchase cost information are necessary to enable reliable decisions.

Appendix B: Survey of Fleet Management with Respect to Multiple Disasters Scenarios

(This is a copy of the survey distributed to the various respondents.)

IRB# 2012-79 Approved 04-19-2012

Dear Participants,

The University of Texas at Tyler (UT Tyler) is currently conducting a research study entitled "Equipment Replacement/Retention Decision Making" sponsored by TxDOT. Maintenance of a robust TxDOT vehicle fleet is essential to accomplishing the daily departmental mission but costly. On one hand, reductions in fleet costs are potentially beneficial to the department as a whole and thereby beneficial to the taxpayers of the State of Texas. On the other hand, not being able to respond adequately under disaster/emergency conditions is unacceptable and therefore maintaining a fleet robust enough to capably respond in a multi-event contingency is also critical. The purpose of this online survey is to comprehensively review and synthesize state-of-the-practice of current fleet management, and describe how other state DOTs and major metropolitan governments provide their fleets to handle multiple disaster scenarios. The responses will be analyzed all together, providing full anonymity for all respondents, and the results will be of interest to many at the state departments of transportation, and other institutions with opportunity for policymaking in the fleet management and transportation arenas.

The online survey through Qualtrics will take approximately 20 minutes to complete. The survey will ask questions about how your state DOT and major metropolitan governments provide fleets to handle multiple disasters. No names or other identifying information will be used in preparing the data for analysis. There are no risks involved in participation in this study and no direct benefits. You are not obligated to participate in the survey and you can stop at any time. However, *your input and opinions are VERY IMPORTANT and HIGHLY APPRECIATED*, since it is critical that all perspectives and state DOTs' best fleet management practices with maintaining a fleet robust enough to capably respond in a multi-event contingency be represented and identified in this survey.

If you have any questions or comments about this study, please feel free to contact me personally at (903) 565-5711. If you have any questions or concerns about your rights as a research participant, please contact Gloria Duke, PhD, RN, Chair of UT Tyler's Institutional Review Board for the Protection of Human Research Protection Information, (903) 566-7023. Your completion of the survey indicates your willingness to participate in the study.

Thank you very much for your time and cooperation.

Sincerely,
Wei (David) Fan, Ph.D., P.E.
Associate Professor

Overview of Disasters

Types of Disasters and Severity

1. Which types of disasters is your agency equipped to respond to? (Please check all that apply)
    a. Hurricanes
    b. Fires
    c. Floods
    d. Epidemics/Biological Attacks
    e. Major Organized Crime
    f. Radiation/Nuclear
    g. Hazardous Material Leaks
    h. Winter Storms
    i. Earthquakes
    j. Other
2. What is the frequency that your agency responds to Hurricanes per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
3. What is the frequency that your agency responds to Fires each year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
4. What is the frequency that your agency responds to Floods each year?
    a. Less than 1 per year
    b. 1 - 2 per year
    c. 4 - 6 per year
    d. More (please specify)
5. What is the frequency that your agency responds to Epidemics/Biological Attacks each year?
    a. Less than 1 per year
    b. 1- 2 per year
    c. 4 - 6 per year
    d. More (please specify)
6. What is the frequency that your agency responds to Major Organized Crime per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
7. What is the frequency that your agency responds to Radiation/Nuclear Leaks per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year

    d. More (please specify)
8. What is the frequency that your agency responds to Hazardous Material Leaks per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
9. What is the frequency that your agency responds to Winter Storms per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
10. What is the frequency that your agency responds to earthquakes per year?
    a. Less than 1 per year
    b. 1 - 3 per year
    c. 4 - 6 per year
    d. More (please specify)
11. What is the typical severity of Hurricane disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
12. What is the typical severity of Fire disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
13. What is the typical severity of Flood disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
14. What is the typical severity of Epidemics/Biological Attacks? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
15. What is the typical severity of Major organized crimes? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
16. What is the typical severity of Radiation/Nuclear Leak disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
17. What is the typical severity of Hazardous Material Leak disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity

    c. Extreme Severity

18. What is the typical severity of Winter Storm disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
19. What is the typical severity of Earthquake disasters? (Please check all that apply)
    a. Minor Severity
    b. Average Severity
    c. Extreme Severity
20. Which type of disaster is your agency most concerned about? (Please Indicate why)
21. Any other comments regarding disasters your agency is equipped to respond to?

Disaster Roles

22. What is the role(s) of your agency in disaster response? (Please indicate which role takes precedence)
23. Any other comments regarding the role(s) of your agency in disaster response?

Active Programs to Increase Disaster Readiness

24. What is your agency doing to increase disaster readiness?
25. What prompted your agency to increase disaster readiness?
    a. State Government Request
    b. Took Initiative
    c. Other
26. In how many years does your agency expect to have completed these increases?
    a. 1 year
    b. 2 - 3 years
    c. 4 - 6 years
    d. 7 or more
27. Any comments regarding your agencies preparedness to respond to multiple simultaneous disasters?

Historical Data

Historical Disaster Data

28. Historically, what types of disaster recovery efforts has your agency been part of? (Please check all that apply)
    a. Hurricanes
    b. Fires
    c. Floods
    d. Epidemics/Biological Attacks
    e. Major Organized Crime
    f. Radiation/Nuclear
    g. Hazardous Material Leaks
    h. Winter Storms
    i. Earthquakes
    j. Other
29. Please list specific disasters (including dates)
30. Any comments regarding these disasters?

Historical Role(s)

31. What role(s) did your agency play in that recovery effort?
32. If your agency played multiple roles, specify which one took precedence (and why)
33. Any other comments regarding role(s) played during historical disaster responses?

Comparison of Defined to Actual Role(s)

34. Did the actual role(s) played differ from the assigned role(s)?
    a. Yes
    b. No (Why)
35. Is the different role(s) incorporated into your mission statement for disaster response as of now?
    a. Yes
    b. No (Why)
36. Any other comments regarding differing of assigned role(s) to performed roles?

Unexpected Role(s)

37. Were there any roles not given to your agency that you assisted with?
    a. Yes (What were they)
    b. No
38. Why did you assist with the extra role?
    a. Governor/Presidential Order
    b. Assistance requested by manager of responsible agency
    c. Took Initiative

39. To what level was your agency prepared to give this extra assistance?
    a. Unprepared
    b. Mediocrely prepared
    c. Somewhat prepared
    d. Very prepared

40. Will your agency be preparing to give this assistance in the future? (Please explain why)

Fleet Management Perspective

Fleet Management/Requisition Initiatives

41. What initiative does your agency have to limit fleet maintenance/reacquisition spending while at the same time provide highest level of fleet robustness?
42. What element does this initiative rely mostly on?
    a. Computers/Algorithm
    b. Human experience/Intuition
    c. Other
43. Does your agency plan to switch to a different method or stay with the one in place?
    a. Yes(Please explain why)
    b. No
44. Any other comments regarding fleet maintenance/reacquisition spending?

Unavailability of Funds

45. Does your agency have protocol to handle unavailability of funds to reach the desired outcome of the initiative, if a budget shortage where to occur?
    a. Yes
    b. No
46. What type of fiscal strategy does this protocol represent?
47. Any other comments regarding protocol about unavailability of funds?

Disaster Preparedness on Decision Making

48. Is disaster preparedness taken into account when making fleet maintenance/reacquisition decisions?
    a. Yes
    b. No
49. How much of a priority is it?
    a. Not very important
    b. Somewhat important
    c. Very important
50. Any other comments regarding disaster preparedness influencing fleet maintenance/reacquisition decisions?

Increasing Disaster Preparedness Levels

51. What does your agency do to increase disaster preparedness levels from a fleet management perspective?
52. Where did your agency get the authority to implement the program(s)?
    a. Government request or mandate
    b. Internally generated idea
    c. Inspiration from other agency (which one)
53. How well does this work?

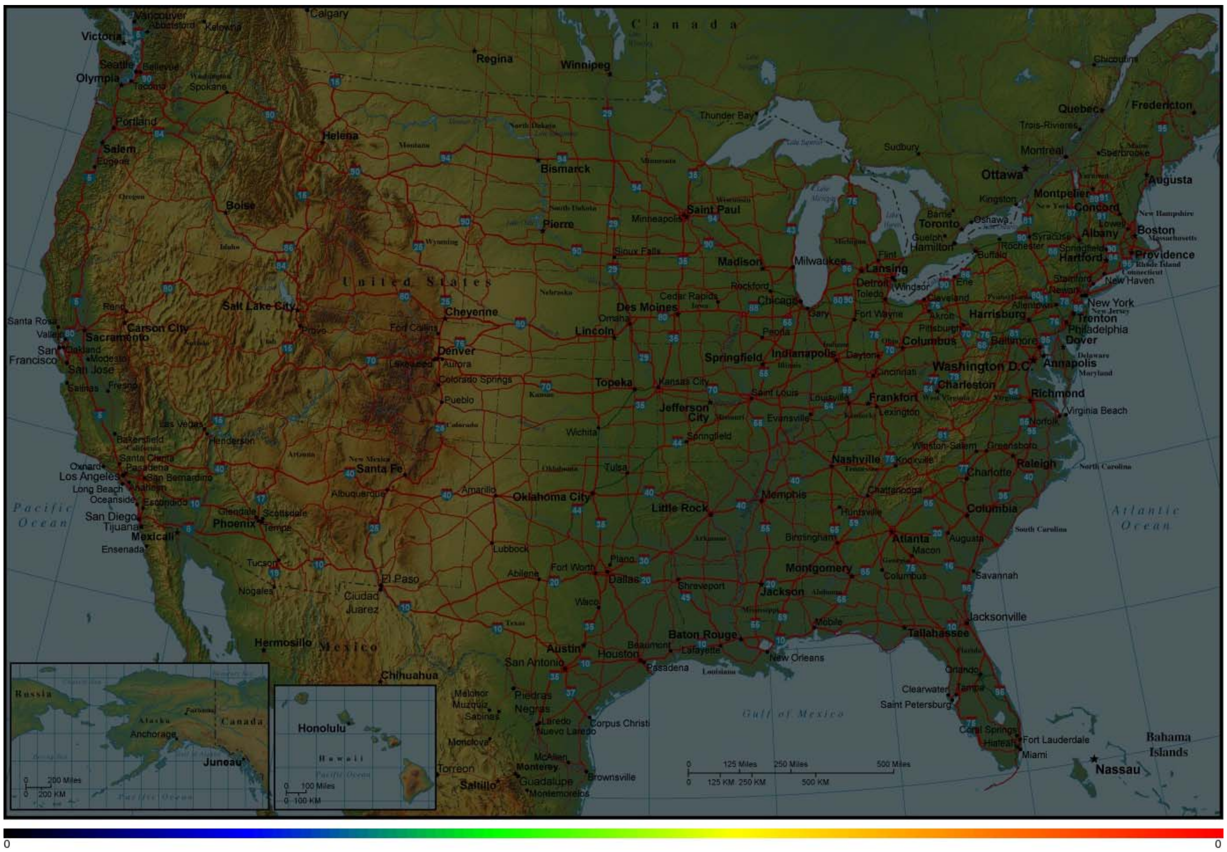
    a. Poorly
    b. Average
    c. Excellently
54. Are there any plans to change this in the future?
    a. Yes (To what)
    b. No
55. Any other comments regarding disaster preparedness from a fleet management perspective?

Cost Benefit Analysis

56. What kind of cost benefit analysis are undertaken to balance non-critical disaster response concerns with limited budgets?
57. Which has precedence?
    a. Non-critical disaster response
    b. Limited budget
    c. Other
58. Any other comments regarding cost benefits analysis between non-critical disaster response and limited budgets?

Geographical Survey

59. Please indicate the area where the most severe disasters which you encounter are located or the area which your agency is accountable for.



Thank you for your participation in this survey. Your time and input are extremely appreciated. If you have any final remarks about Equipment Replacement/Retention Decision Making with respect to disaster preparedness, which were not discussed in the survey, please indicate them below.

Again, thank you and have a great day.

Appendix C: Equipment Replacement Decision Making: Challenges and Opportunities

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Word Count: 6765 words + 2 figures + 1 table = 7515 word-equivalents

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