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FORECASTING MODELS TO INVESTIGATE FUTURE UNCERTAIN PURCHASE COSTS DUE TO TECHNOLOGY CHANGES, AND ESTIMATE DOWN TIME COSTS AND OPERATING AND MAINTENANCE COSTS

Center for Transportation Research
Randy Machemehl
Mason Gemar

The University of Texas at Tyler
Wei Fan

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Performing Organization: Center for Transportation Research The University of Texas at Austin 1616 Guadalupe, Suite 4.202 Austin, Texas 78701	**Sponsoring Organization:** Texas Department of Transportation Research and Technology Implementation Office P.O. Box 5080 Austin, Texas 78763-5080
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Chapter 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.

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.

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 class codes. 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 1.1.

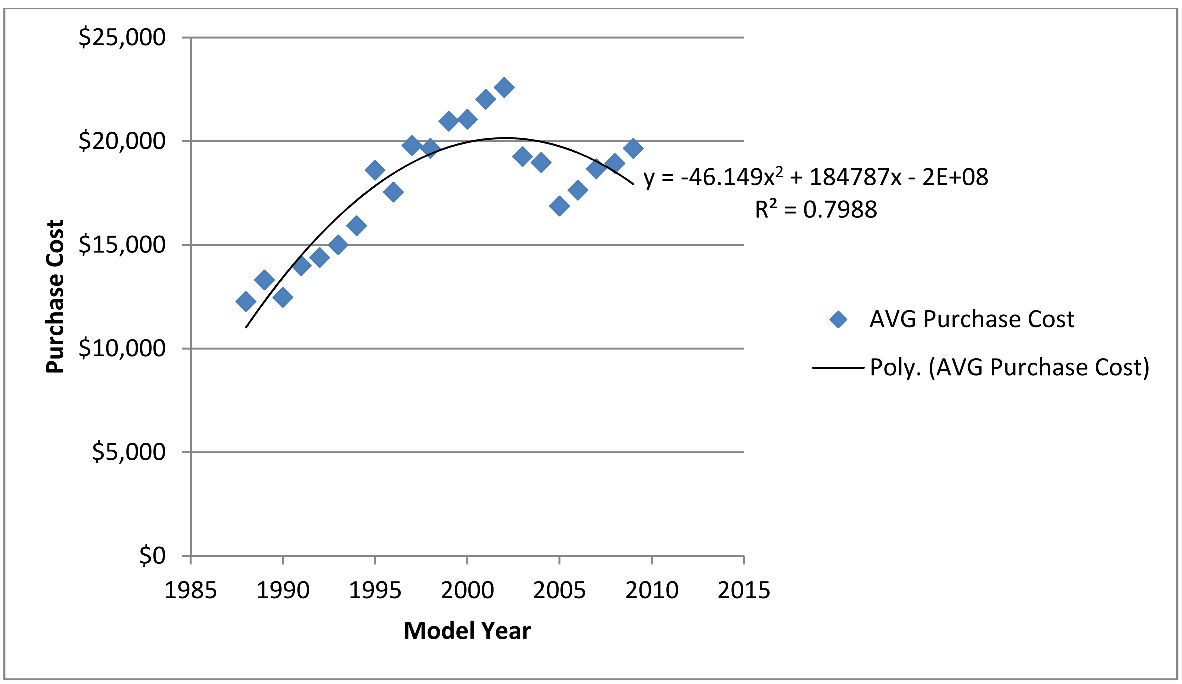


Figure 1.1 Average Purchase Cost Versus Model Year with Best-fit Model for Classcode 430070 (Light Duty Truck)

Note that Figure 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.

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.

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.

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 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.

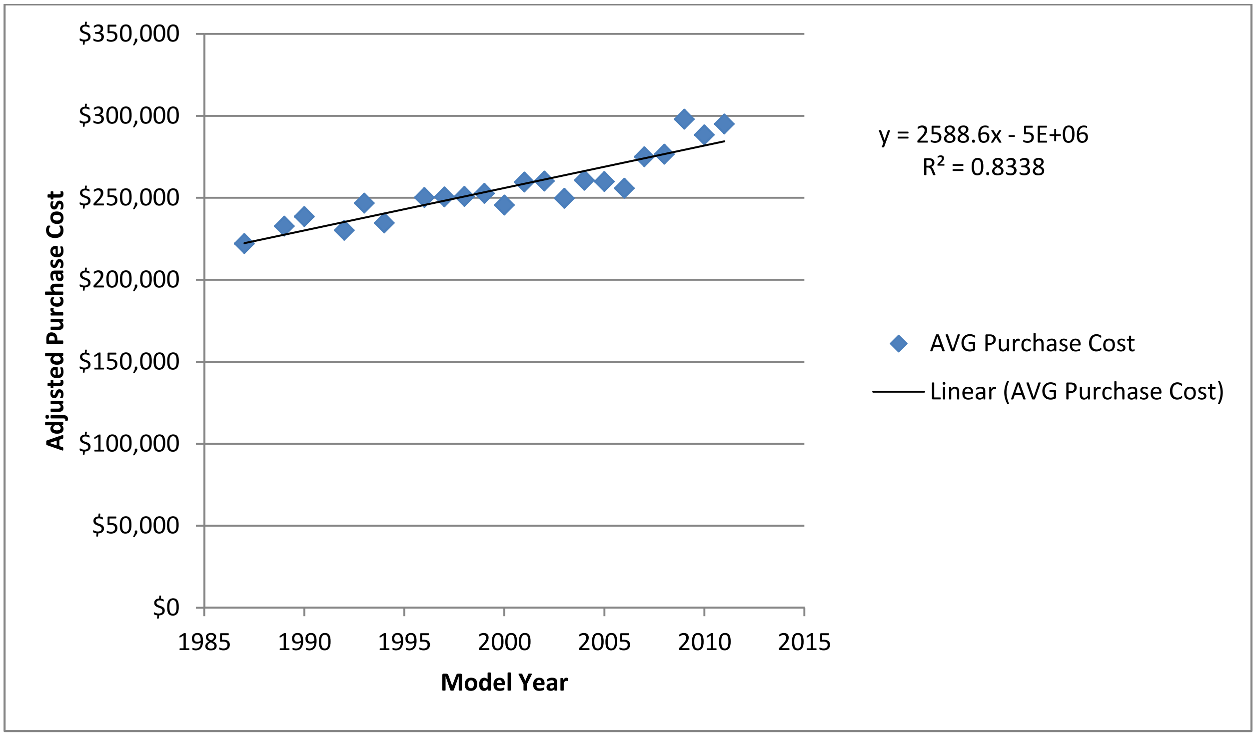


Figure 1.2 Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 75010 (Excavator, Telescoping Boom, Carrier Mounted)

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 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.

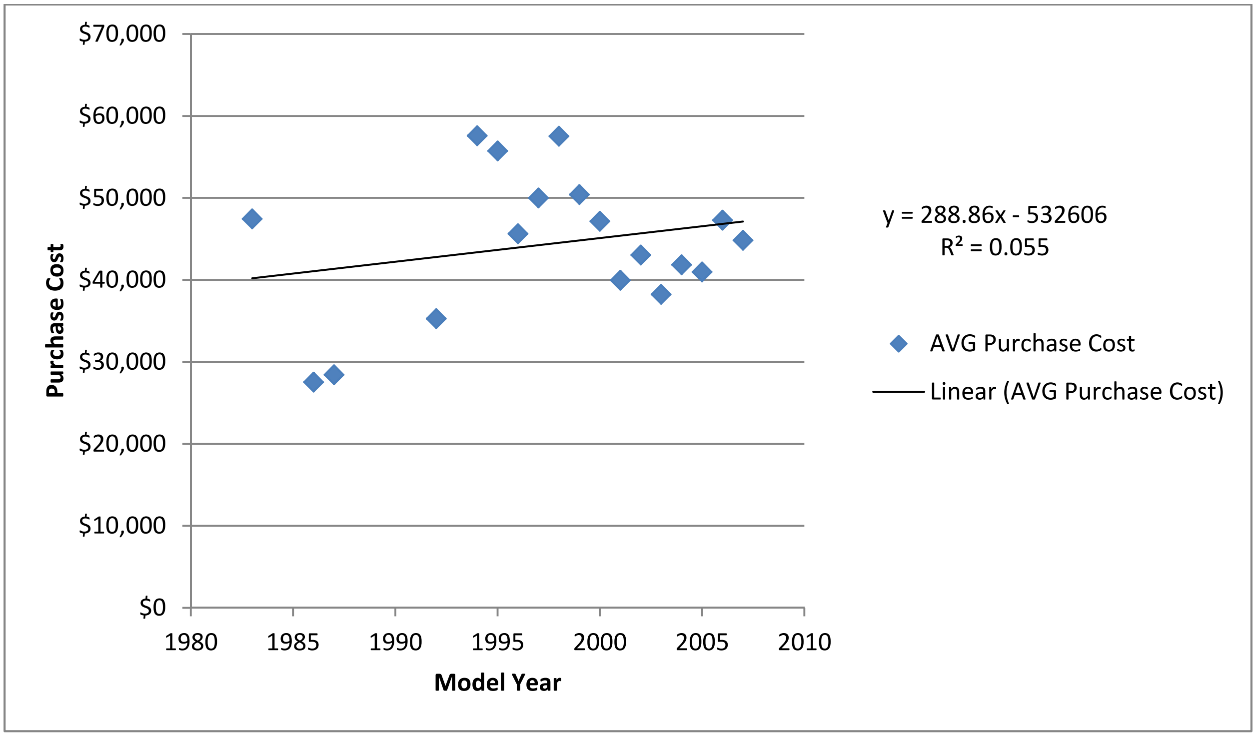


Figure 1.3 Average Adjusted Purchase Cost Versus Model Year with a Linear Model for Classcode 115000 (Loader, Pneumatic Tired, Skid Steer)

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:

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

As such, adjusted purchase cost values falling outside 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.

1.3.3. Implementing the Algorithm

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

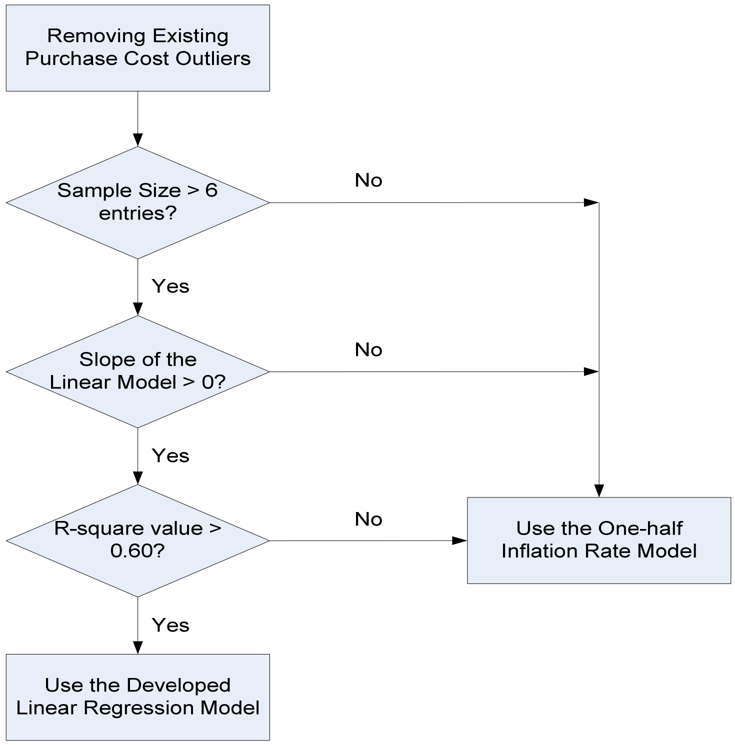


Figure 1.4 Flow Chart of the Purchase Cost Forecasting Algorithm Software Implementation

As shown in Figure 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.

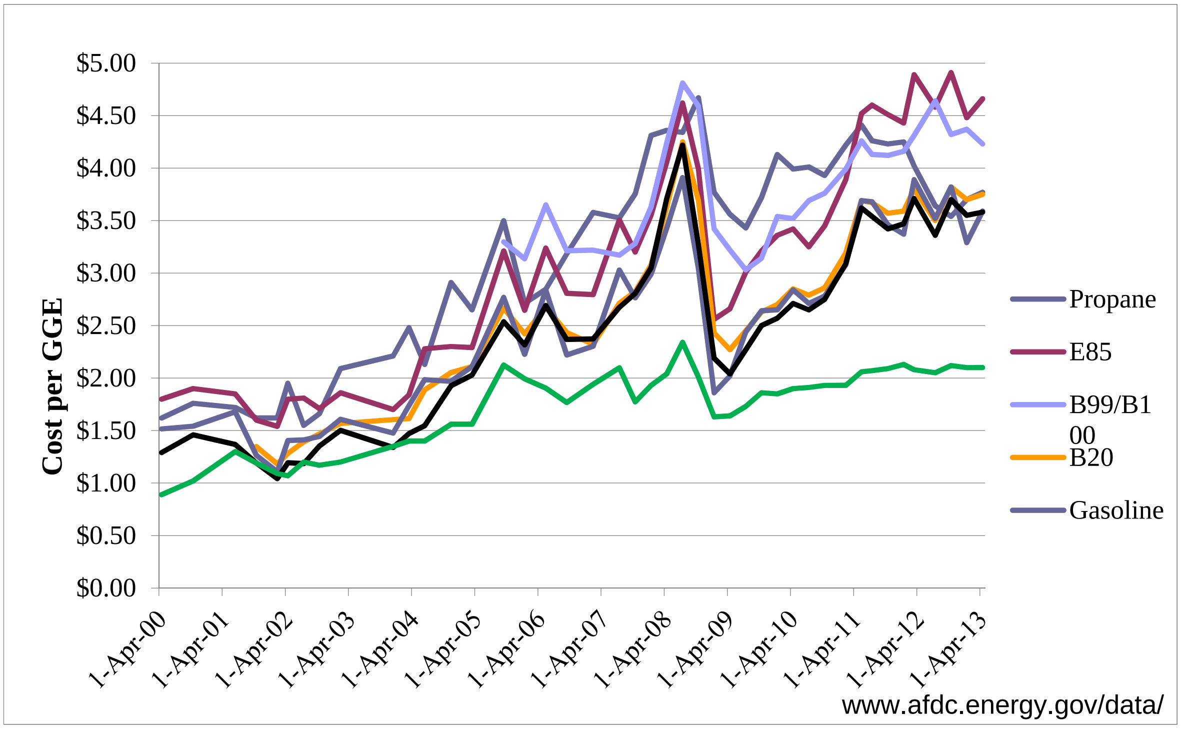
1.3.4. Reviewing the Results

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 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 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.



Source: Alternative Fuels Data Center (AFDC) of the U.S. Department of Energy

Figure 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 CAFE 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.

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.

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.

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.

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.

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.

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.

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.

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 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 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 2.2 illustrates the fuel prices from Table 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 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-B100)	$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 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 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 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 $3.5 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 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.

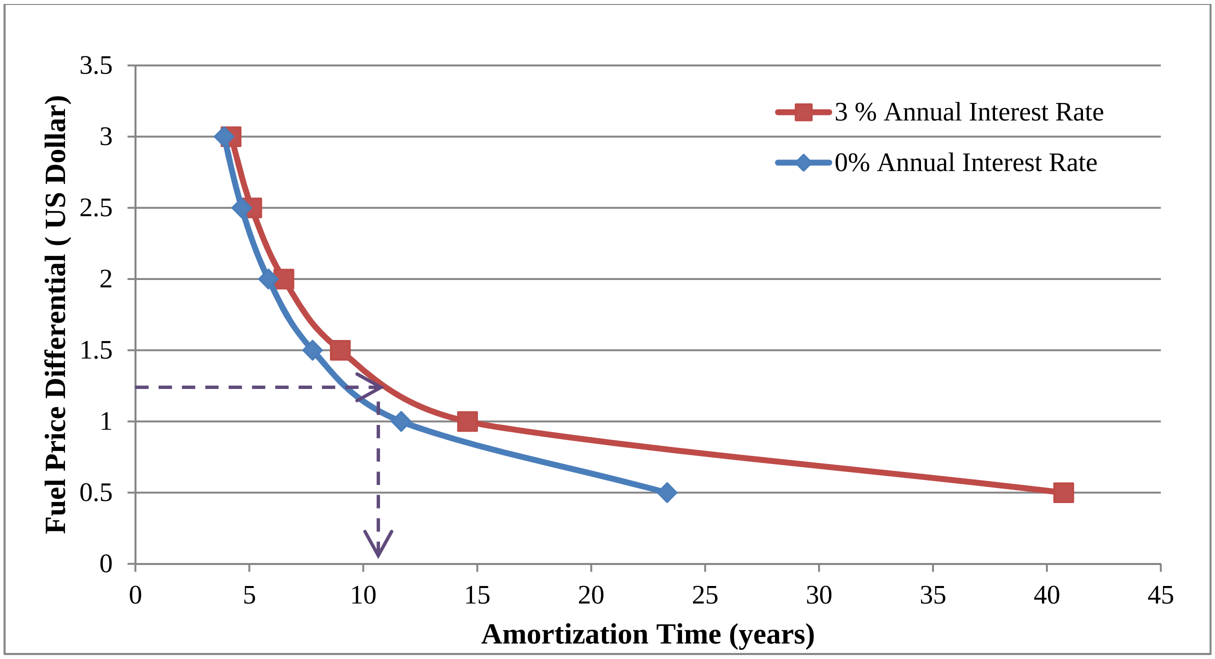


Figure 2.2 Price Differential of CNG With Respect to Gasoline Versus Cost Amortization Time for Sedan Cars

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 2.3 shows the cost amortization time for light-duty trucks for varying fuel price differentials.

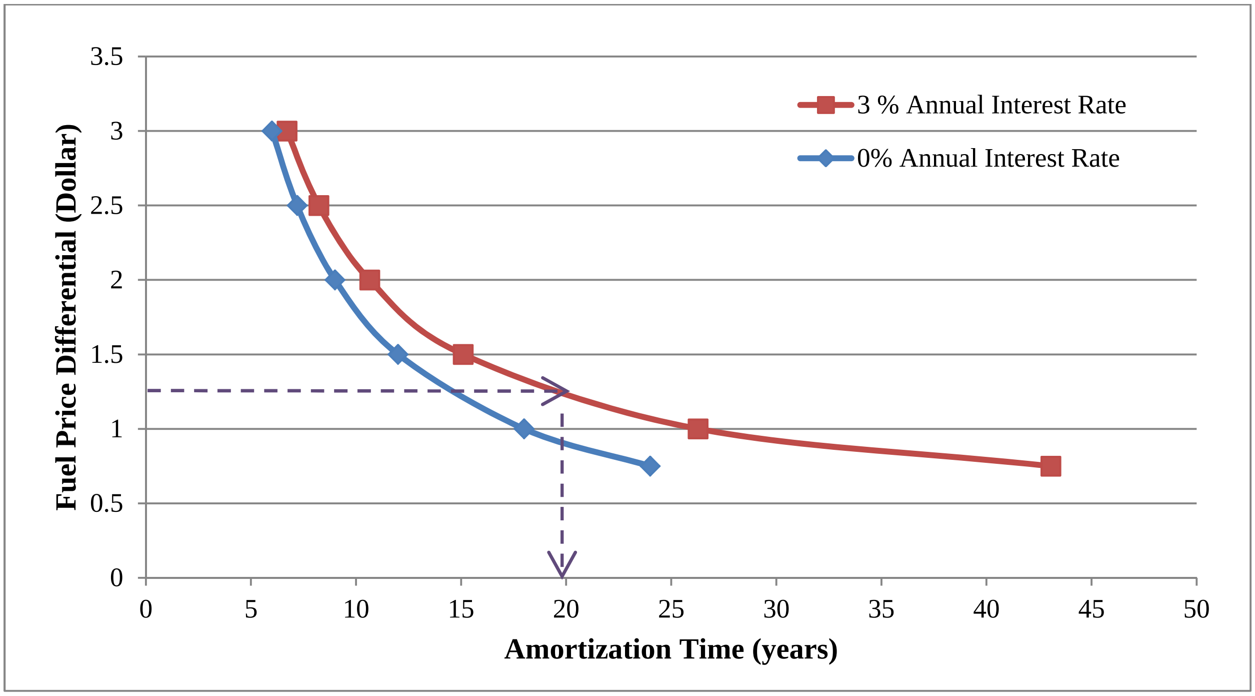


Figure 2.3 Price Differential of CNG With Respect to Gasoline Versus Cost Amortization Time for Light Trucks

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 2.4 and 2.5 show cost amortization time against fuel price differential for LNG enabled heavy-duty vehicles.

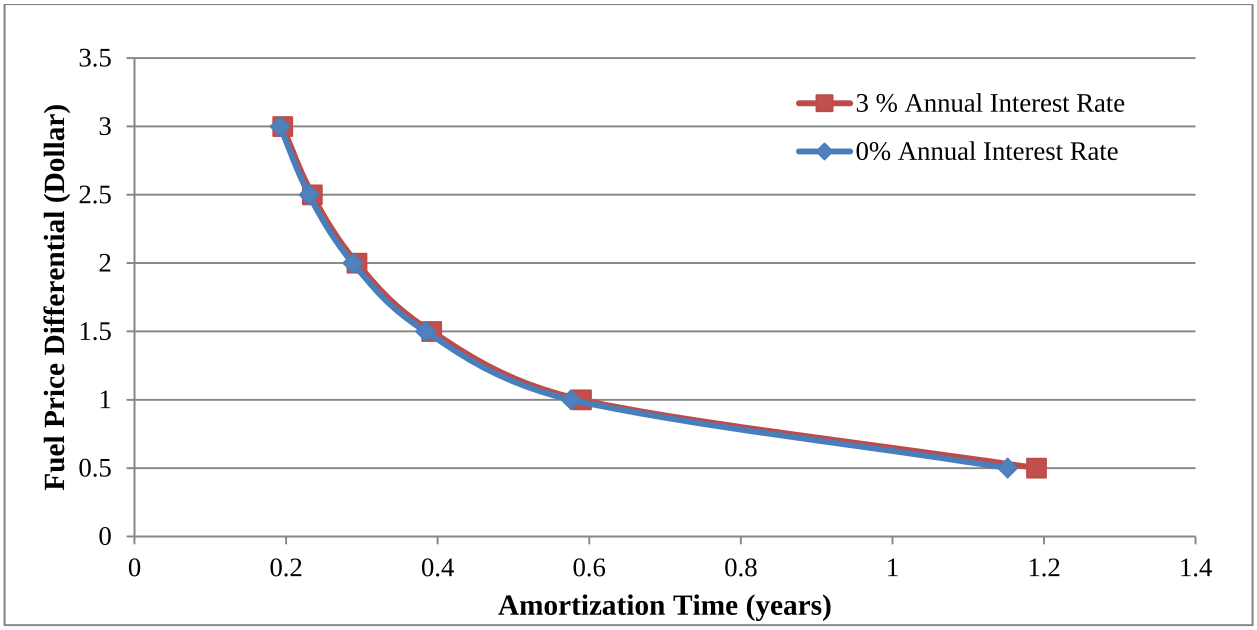


Figure 2.4 Fuel Price Differential of LNG With Respect to Diesel Versus Cost Amortization Time for Heavy Duty Vehicles for a Conversion Cost of US$8000

In Figure 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 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 2.4 and 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.

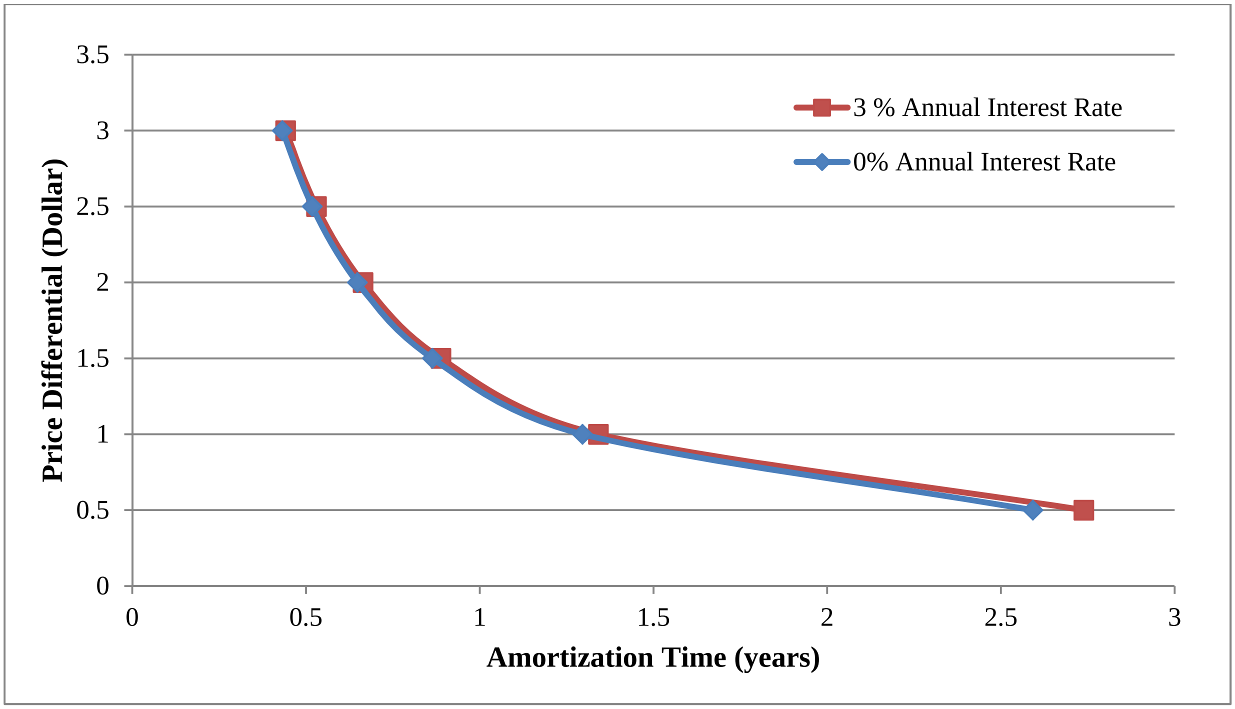


Figure 2.5 Fuel Price Differential of LNG With Respect to Diesel Versus Cost Amortization Time for Heavy Duty Vehicles for a Conversion Cost of $18,000

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.

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 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.

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.

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 that 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 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 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 3.1 below.

Table 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

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

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)			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 POWERED	$50	$7.00	3

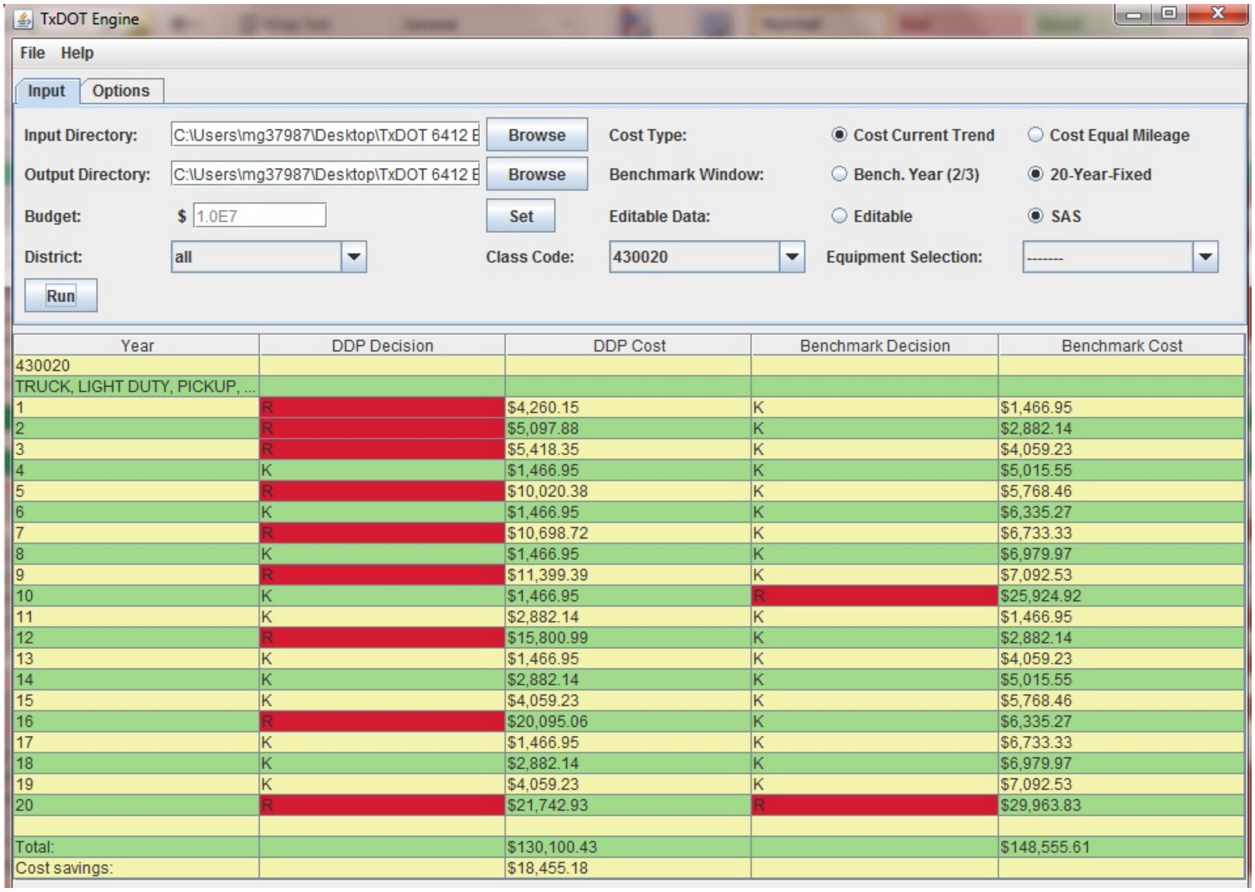
Due to the fact that some vehicles and equipment units have large amounts of down time recorded in the database, these rates can have a substantial impact on estimates of O&M costs. The detailed assessment of these O&M costs was undertaken as part of evaluating preliminary optimization results.

Chapter 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.

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 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 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.

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 4.2.

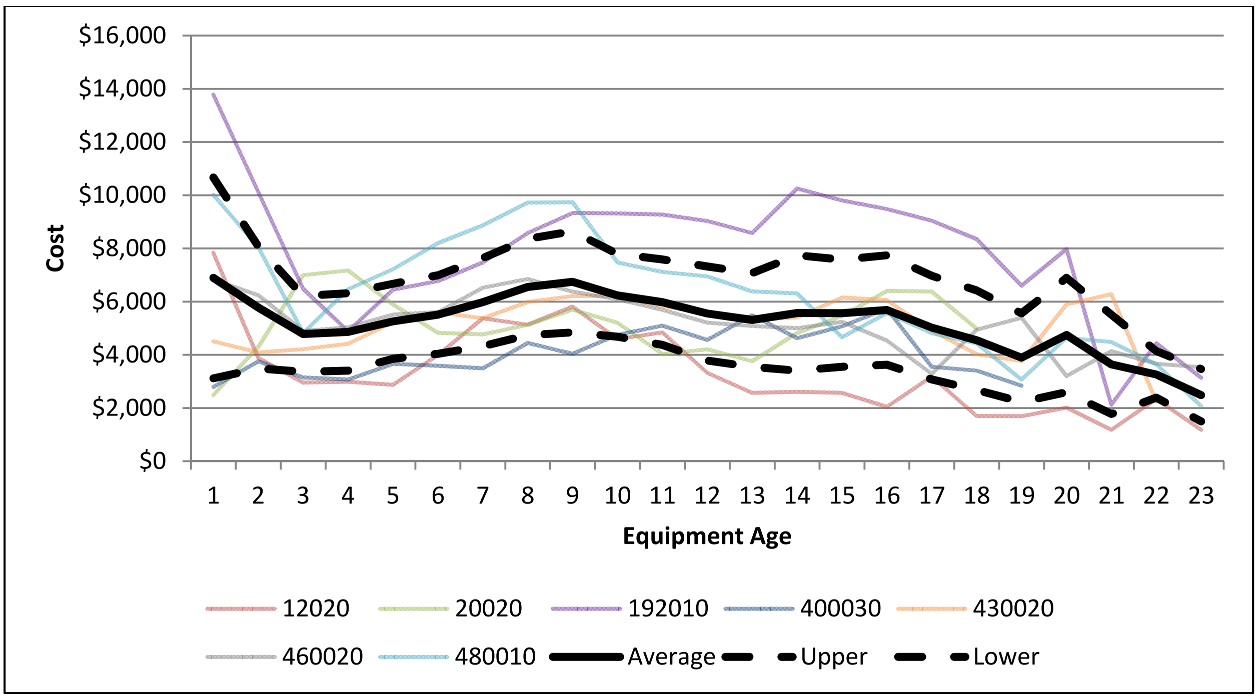


Figure 4.2 Original Average O&M Costs for Select Light Duty Vehicles

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 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.

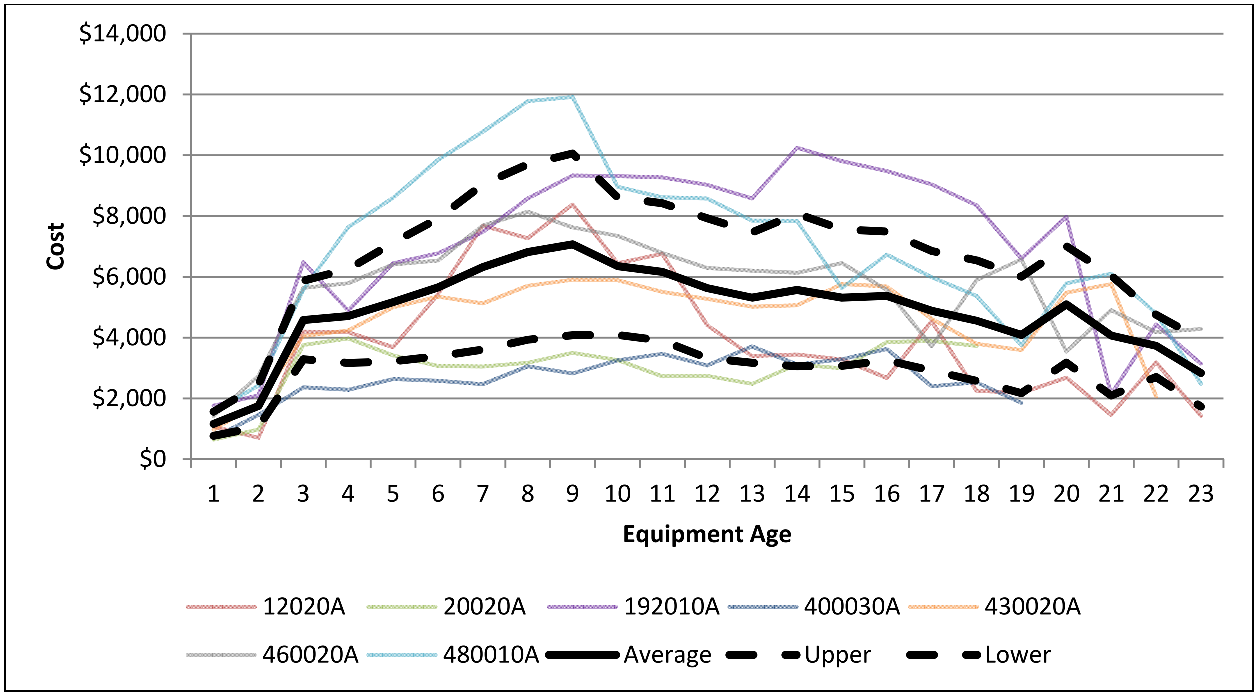


Figure 4.3 Adjusted Average O&M Costs for Select Light Duty Vehicles

Likewise, the analysis of select heavy duty vehicles revealed similar trends. Figure 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.

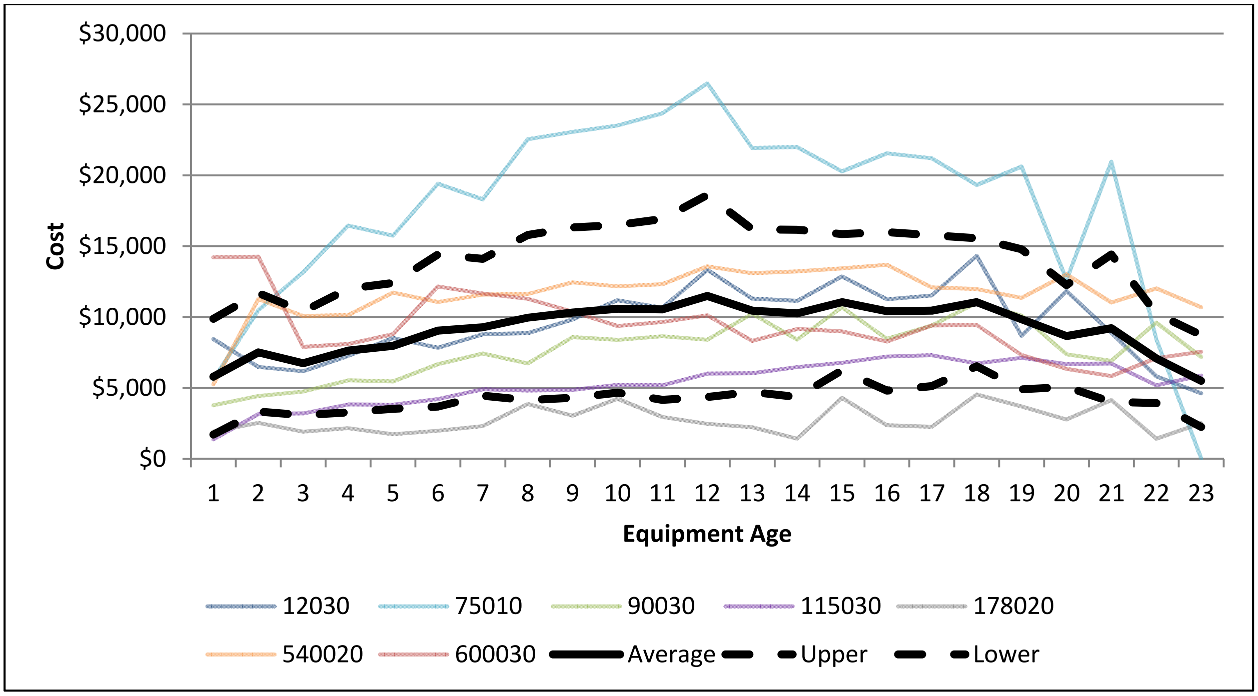


Figure 4.4 Original Average O&M Costs for Select Heavy Duty Vehicles

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 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.

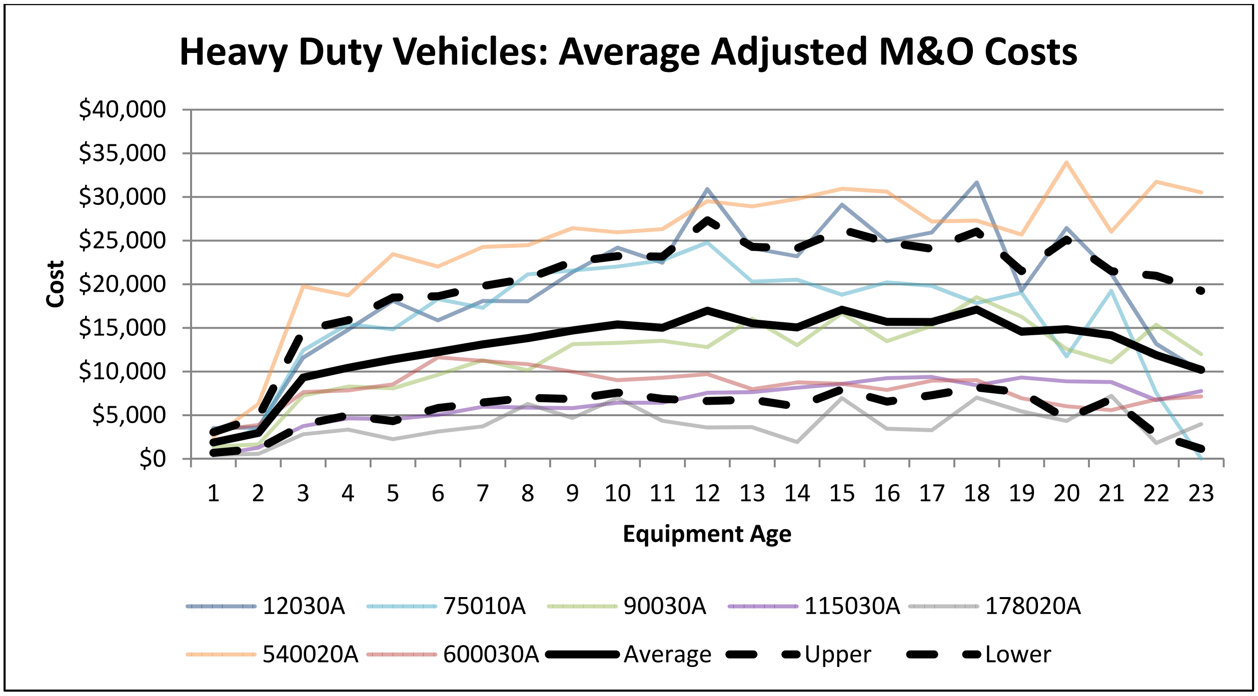


Figure 4.5 Adjusted Average O&M Costs for Select Heavy Duty Vehicles

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.

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 4.6.

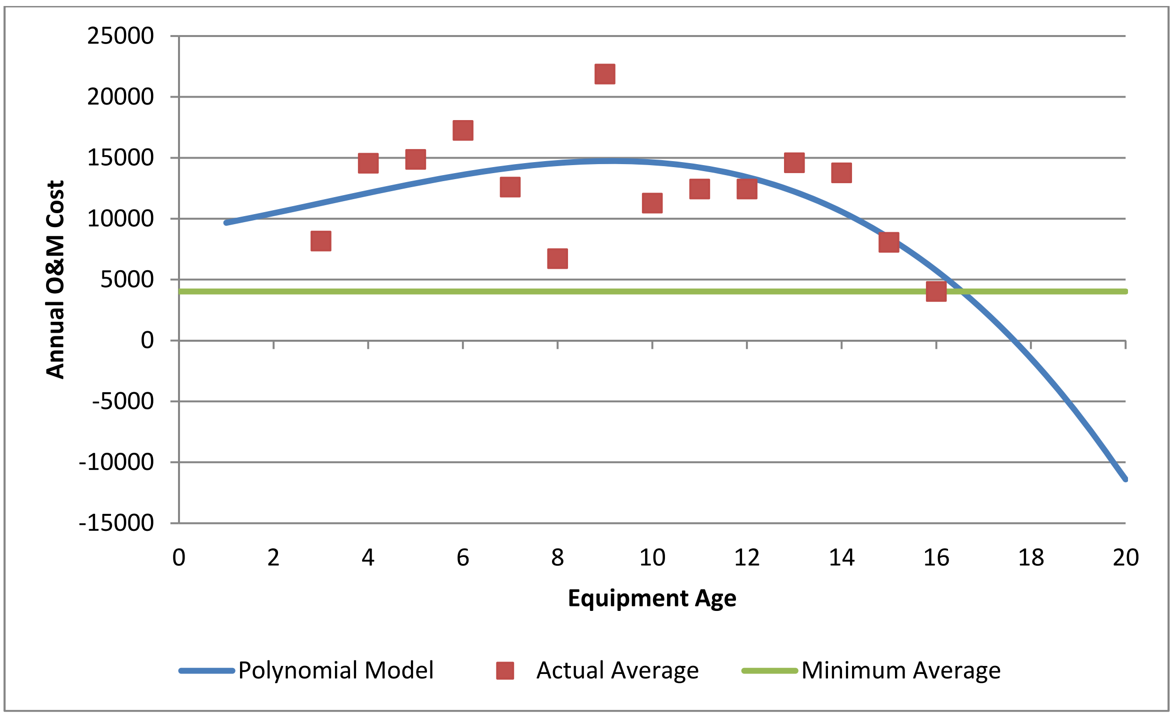


Figure 4.6 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 400020 (Light Duty Truck, 4-WD Pickup)

Note that Figure 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., 10^{th} 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 4.7 illustrates this type of trend as identified for classcode 90040.

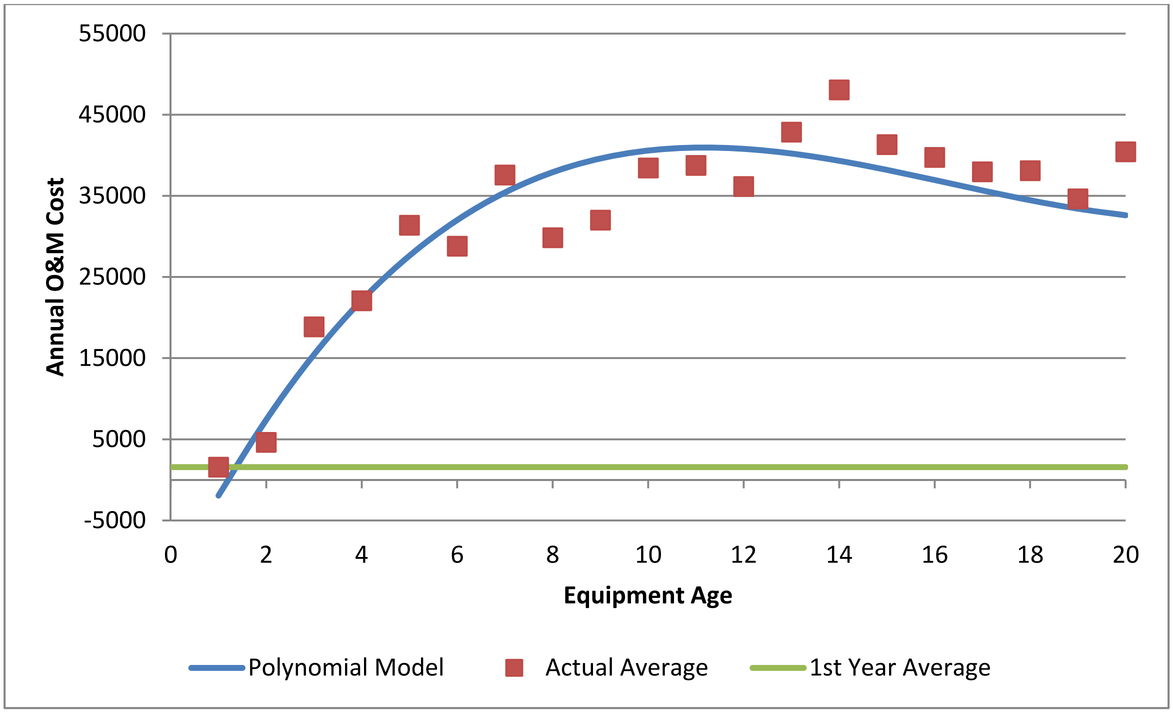


Figure 4.7 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 90040 (Grader, Motor, Class IV)

While Figure 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 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 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 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 4.8.

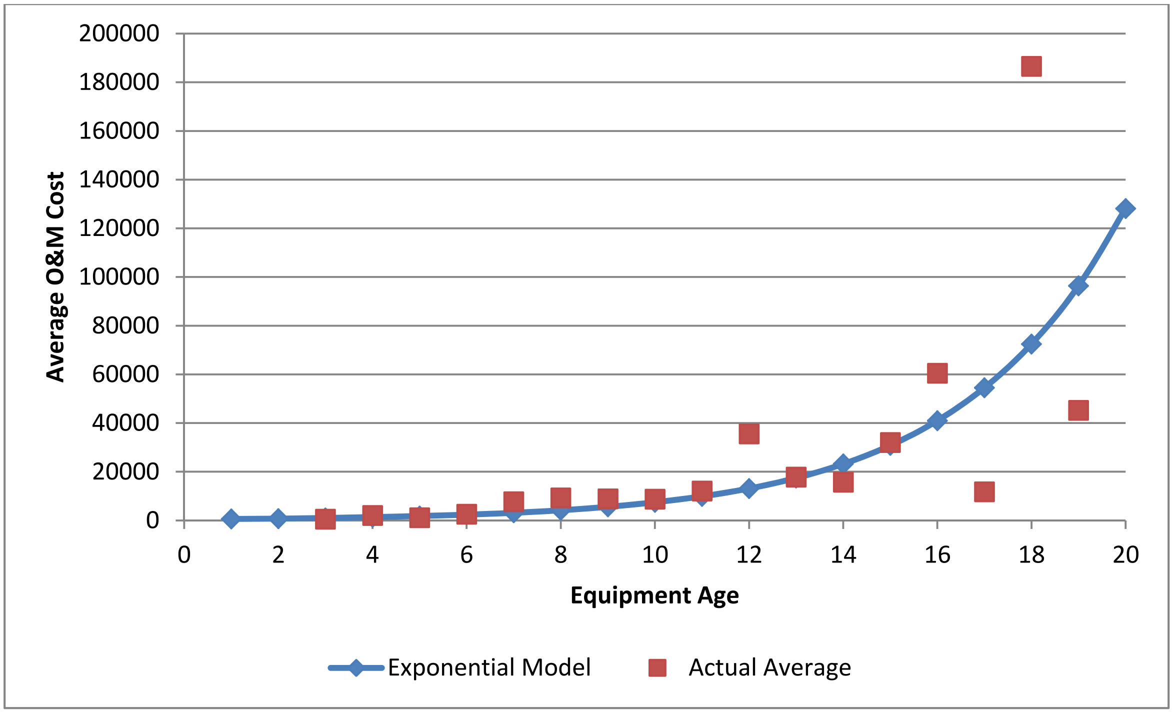


Figure 4.8 Average O&M Cost Versus Equipment Age with Best-fit Model for Classcode 520020 (Truck, Conventional Dump)

As can be seen in Figure 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 or an Excel file 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.

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 4.9.

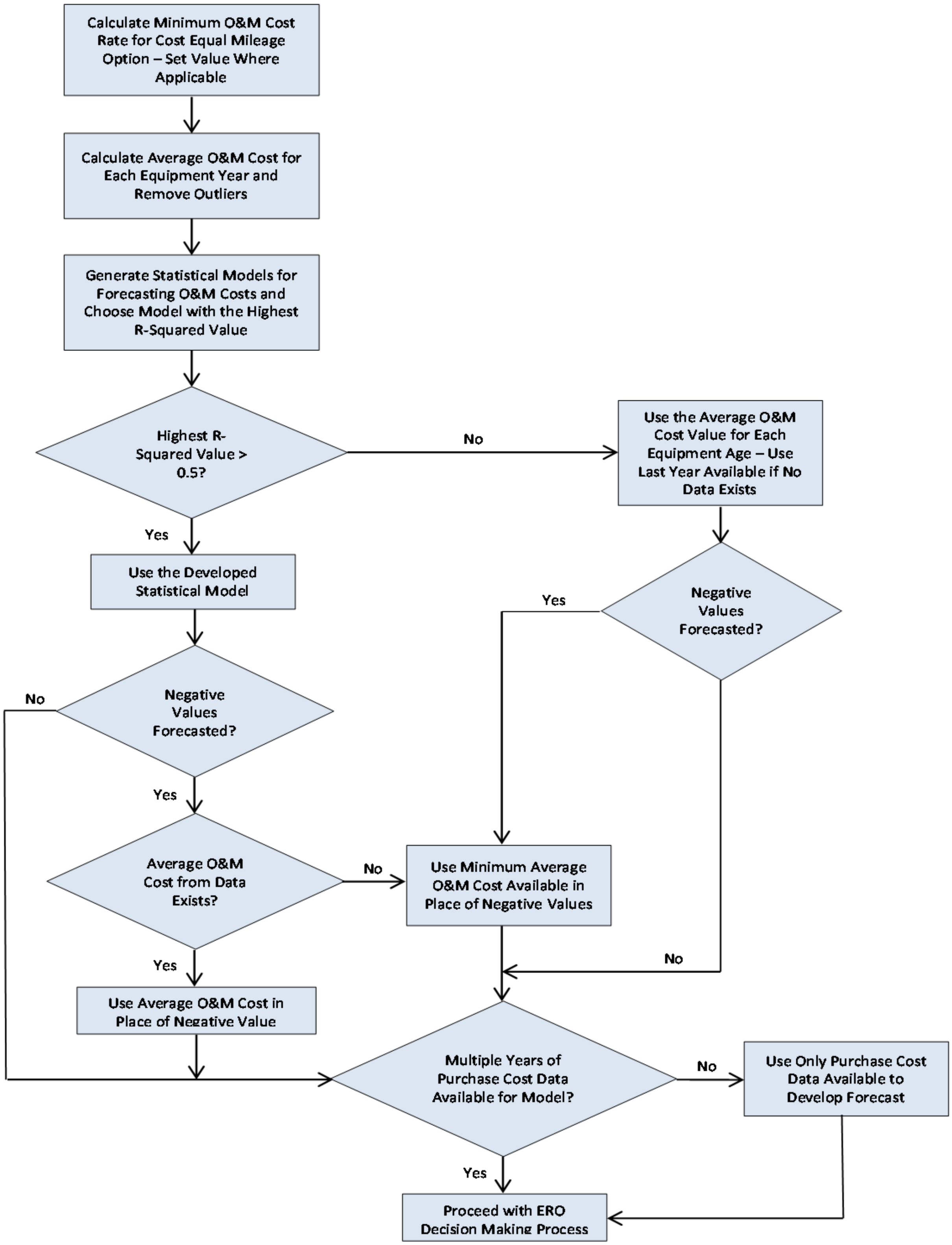


Figure 4.9 Flow Chart of the O&M Cost Forecasting Algorithm Software Implementation

As shown in Figure 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.

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.

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.

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