AN ABSTRACT OF THE THESIS OF

Phillip Oliver Kriett for the degree of Master of Science in Industrial Engineering presented on January 23, 2009.

Title: Equipment Replacement Prioritization Measures: Simulation and Testing for a Vehicle Fleet

Abstract approved:

David S. Kim

Oregon Department of Transportation (ODOT) Fleet Services manages a fleet that in 2008 included approximately 5,000 pieces of active equipment worth \$340–\$390 million. Every biennium, a fixed budget is available to replace a certain amount of this equipment. This research evaluated various measures for establishing equipment replacement priorities.

A model was developed to simulate the operation of a single equipment class over time, including equipment replacement every two years. Five different equipment classes were simulated using ten measures for establishing replacement priorities. Historical data for these five different equipment classes (provided by ODOT) was used to define various simulation parameters. The effectiveness of each prioritization measure was evaluated using the cost per mile to operate the fleet over the simulated time period.

EQUIPMENT REPLACEMENT PRIORITIZATION MEASURES: SIMULATION AND TESTING FOR A VEHICLE FLEET

by

Phillip Oliver Kriett

A THESIS

submitted to

Oregon State University

in partial fulfillment of
the requirements for the
degree of

Master of Science

Presented January 23, 2009
Commencement June 2009

Master of Science thesis of Phillip Oliver Kriett presented on January 23, 2009.

APPROVED:

Major Professor, representing Industrial Engineering

Head of the School of Mechanical, Industrial, and Manufacturing Engineering

Dean of the Graduate School

I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Phillip Oliver Kriett, Author

ACKNOWLEDGEMENT

The author expresses sincere appreciation to his mentor, Dr. David Kim, for his guidance and insight on this project. He is grateful to the other members of his committee, Dr. David Porter, Dr. B. Starr McMullen, and Dr. Roger Graham. Moreover, he would like to thank Dr. Shawna Grosskopf and Dr. Rolf Fare for giving advice from a different perspective. The author appreciates Tristan Wagner's and Wilson Mbugua's openness for questions. Finally, he would like to thank Oregon Department of Transportation which provided funding for this research.

TABLE OF CONTENTS

Page

TABLE OF CONTENTS (CONTINUED)

Page

LIST OF FIGURES

Figure | Page

LIST OF TABLES

Table Page

LIST OF TABLES (CONTINUED)

LIST OF APPENDIX FIGURES

<u>Figure</u> <u>Page</u>

LIST OF APPENDIX TABLES

LIST OF APPENDIX TABLES (CONTINUED)

Table | Page

EQUIPMENT REPLACEMENT PRIORITIZATION MEASURES: SIMULATION AND TESTING FOR A VEHICLE FLEET

1 INTRODUCTION

In the United States individual state departments of transportation (DOTs) maintain large fleets of equipment. This equipment represents a substantial investment and is a vital set of resources used to maintain roads and highways. An important and difficult challenge of managing such a large amount of equipment is deciding when to replace existing equipment. Such decisions have a clearly documented economic impact, and also affect the ability of the fleet to provide required equipment when needed. The focus of the research presented is the testing and evaluation of simple replacement prioritization measures that utilize only life-to-date equipment cost and usage data. These measures will be used to prioritize equipment replacement candidates within equipment classes as found in the Oregon Department of Transportation (ODOT) fleet. The emphasis on measures that utilize only life-to-date equipment cost and usage data is driven by data available in most equipment management and maintenance systems in use by state DOTs.

ODOT Fleet Services provides management of a fleet, which (in 2008) consisted of approximately 5,000 pieces of active equipment representing $340-$390 million worth of assets. This equipment includes a variety of small and large trucks, cars, as well as heavy machinery such as graders, bulldozers, and many types of tractors, which are separated into different equipment classes. An important feature of many of the more expensive equipment classes (e.g., heavy diesel trucks) in the ODOT fleet is that its members show age dependent use patterns. These use patterns have an impact on fleet costs. Utilization of ODOT equipment, in general, decreases as equipment grows older. The hypothesized reason is that crews who can choose between older and newer equipment to use will more often select newer equipment.

Currently, equipment replacement in ODOT's fleet occurs in regular intervals (every two years), and in general only new equipment units are used as replacements. The total fleet size remains relatively constant over time. Replacement decisions must be made across different equipment classes that have different usage, cost, and longevity. Additionally, the current environment at ODOT and other state DOTs is that replacement decisions are budget restricted.

The approach used in this research to evaluate different replacement prioritization measures is simulation. Part of this procedure uses statistical distributions which are derived from given historical ODOT data. Prior annual usage and cost data compiled for ODOT's fleet are analyzed. Probability distributions representing equipment usage and costs over time in different equipment classes are fitted to the data. Correlations between usage and costs, and correlation over time for usage and costs are computed and represented in the simulations. In order to reflect ODOT fleet management characteristics, the size of a simulated fleet remains constant over time. The replacement of a fixed and limited amount of equipment occurs every two years. Single simulation runs are 500 years in length, and the performance measure utilized is the average total cost per usage unit to operate the fleet. The centerpiece of the simulation is the ability to apply different replacement prioritization measures to the same fleet of equipment under identical circumstances. This makes the recorded performance measures comparable and allows an assessment of the applied prioritization measures.

The remainder of this thesis is organized as follows. In section two we identify the state-of-the-art in equipment replacement models in both practice and in the published research literature. In section three we explain the preparation of data which we have received from ODOT. In particular, the adjustment for inflation, correlation analysis, and distribution fitting are exemplified. The procedure of the simulation is explained and other aspects of the simulation including random variate generation, tested replacement prioritization measures, and designs of experiments are presented. In section four results from the simulation are summarized, analyzed, and presented. In section five we discuss problems and features of this research and in section six our conclusions are presented.

2 LITERATURE REVIEW

Fleet managers and researchers have recognized the problem of equipment replacement for a long time and they have developed a variety of strategies to address it. In order to identify the state-of-the-art in equipment replacement models in both practice and in the published research literature we review published models and studies on the one hand, and also how replacement problems are managed in practice at various state DOTs. This strategy reveals a difference between theory and practice.

2.1 PUBLISHED MODELS AND STUDIES

Our literature review focuses on studies about equipment replacement problems that occur in vehicle fleets. Hence, the main question is how to identify replacement candidates among fleet members so that total fleet costs are minimized. An intuitive method is to define a replacement criterion, e.g. total equipment life time. Multiple ways are published to use such replacement criterion, e. g. as a ranking criterion for replacement candidates. Instead of life time, another group of papers focuses on using repair costs as a helpful measure to support replacement decisions. Papers presenting comprehensive cost minimization models provide fleet specific, detailed solutions rather than suggesting a broadly applicable replacement criterion. In this literature review we take a special interest on equipment replacement models considering decreasing utilization. In the following reviewed publications are analyzed in more detail while a table summarizing most of the results of this review of published literature can be found in the appendix (see Table 29 and Table 30).

2.1.1 Models focusing on life time limits

Assets that exceed the equipment life time limit are candidates for replacement. A ranking can be installed sorting equipment units in descending order from the unit which exceeds the limit most down to the one which exceeds the limit least. One of the most popular approaches to derive life time limits as replacement criteria is single asset replacement analysis which is also known as life cycle cost analysis (LCCA) and which is extensively covered in the engineering economics literature[1]. Eilon et al. (1966) consider acquisition cost, resale value and maintenance cost in order to derive the minimum average costs per equipment year and the corresponding optimal life time limit policy for a fleet of fork lift trucks.

---

[1] See Dhillon (1989) and Grant et al. (1990)

Chee (1975) analyzes the fleet of Ontario Hydro using LCCA and generates optimal life time policies for different equipment classes. Because LCCA gives only one replacement criterion – namely the life time limit – for a whole equipment class, Chee (1975) proposes to also consider repair costs for individual equipment units. As a result, repair cost limits are computed in addition to life time limits. If a fleet member stays within the repair cost limits for each year, it is replaced only after reaching the economic life of its class. Similarly, Weissmann et al. (2003) apply LCCA on individual equipment units of the fleet of Texas DOT and compare equipment units within the same class in order to determine optimal moments of replacement. Their study proposes replacement decisions based on a multi attribute ranking. The multi attribute ranking considers LCCA results, operation costs, repair costs and usage in order to assign replacement priorities to equipment units. Ayres et al. (1978) normalize annual maintenance costs by mileage and current acquisition costs and use this inflation independent parameter for LCCA. The normalization is assumed to fix the problem of incomparability because differences in complexity and function of equipment units. Thus, the presented method allows to make replacement decisions fleet wide – ignoring the fact that a fleet consists of different equipment classes.

2.1.2 Models focusing on repair cost limits

Another popular replacement criterion is repair costs. Some literature provides evidence that repair cost limit policies entail advantages over life time limit policies. Drinkwater et al. (1967) analyze data from army vehicles. They find age dependent frequencies for repair visits per year and distributions for repair costs per visit. Drinkwater et al. (1967) use this information in a combination of dynamic programming and Monte Carlo simulation in order to determine optimal repair cost limits. They find out that the determined repair cost limit policy leads to financial savings compared to a LCCA based life time limit policy and compared to an experience based repair cost limit policy which was previously applied on the army fleet. A similar result comes from Love et al. (1982) who work on fleet data from Postal Canada and compare life time limit policies with repair cost limit policies. They derive life time limits analytically and repair cost limits are generated in a Markov simulation. Applied to the Postal Canada fleet the repair cost limit policy is superior to the life time limit policy. Instead of using repair cost limits for repairs that have occurred, Hastings (1969) derives repair cost limits for estimates of future repair costs. He assumes that before any repair measure is conducted, assets run through an inspection and repair costs are estimated. The actual repair is only undertaken if estimated costs are smaller than the derived repair cost limit. Another approach which comes from Nakagawa et al. (1974) does not focus on repair costs but on repair time. Nakagawa's policy defines a limit for the time a broken unit of equipment spends in repair measures. The repair time limit is derived by minimizing expected costs per unit time over an infinite time span.

2.1.3 Comprehensive cost minimization models

Other approaches widen the problem of optimal replacement to the problem of optimal buy, operate and sell policies. Simms et al. (1984) have detailed data from an urban transit bus fleet. Equipment units in this fleet are operated at different levels and perform different tasks as a function of age or cumulative mileage, subject to varying capacity constraints. Moreover, newer equipment units have different acquisition and operating cost structures than older less sophisticated fleet members. By applying a combination of dynamic programming and linear optimization an optimal buy, operate and sell policy is derived for the investigated fleet. Similar to Simms et al. (1984), Hartman (1999) is looking for the minimum cost replacement schedule and associated utilization levels for a multi asset case – emphasizing that utilization is a decision variable and not a parameter. The author examines the problem of simultaneous determination of asset utilization levels as well as replacement schedules while the total costs of assets that operate in parallel are minimized. A linear program that considers dependency of operating costs on utilization levels and dependency of utilization levels on a deterministic demand solves the problem. Hartman (2004) faces the same problem as Hartman (1999) but now asset utilization levels meet a stochastic demand. In a simplified case with two equipment units and parallel operation of both assets the author determines the optimal replacement schedules and utilization levels for both individual vehicles by applying dynamic programming. Simms et al. (1984), Hartman (1999) and Hartman (2004) face complex equipment replacement, operating and scheduling problems occurring in vehicle fleets. They do not promote particular replacement prioritization criteria but present optimization methodologies that lead to cost efficient results for specific fleets.

2.1.4 Models considering decreasing utilization

While the type of replacement methodology is one focus of our literature review another focus is on utilization levels. We attach importance to the finding that utilization of ODOT equipment is decreasing with equipment’s age because constant utilization is a widely spread assumption made by replacement models in literature, particularly LCCA. As alluded, Simms et al. (1984) derive an optimal buy, operate and sell policy for an urban transit bus fleet whose members are operated at different levels depending on equipment age. In detail, Simms et al. (1984) reduce the problem to two levels of utilization: young buses are operated at a constantly high level meeting the base demand and utilization is constantly low for buses older than ten years because they are only used to match peak demand in public transportation.

Beside Simms et al. (1984) who indicate the problem of decreasing utilization we have found two other publications which directly address this topic. Redmer (2005) derives the optimal life time limit for a freight transportation fleet which shows decreasing utilization as equipment grows older and constant utilization levels within age classes. The basis of his model is the LCCA approach from Eilon et al. (1966) which assumes constant utilization, and thus, is not directly applicable on the fleet analyzed by Redmer (2005). Eilon et al. (1966) consider analyzed costs per unit time. Redmer (2005) points out that this is the reason why the model from Eilon et al. (1966) provides life time limits bounding for infinity when it is fed with fleet data showing decreasing utilization. Instead of using costs per unit time, Redmer (2005) modifies the LCCA approach from Eilon et al. (1966) to that costs are given per kilometer. As a result, discounted costs of exploitation and ownership per kilometer are minimized over replacement age and a feasible, cost minimizing life time limit is provided. The second study underlining the importance of decreasing utilization levels over equipment age is written by Buddhakulsomsiri et al. (2006). Their model is adopted from Hartman (1999). A major difference is that in Hartman's model utilization is defined as a decision variable, whereas in the study from Buddhakulsomsiri et al. (2006) it is assumed that utilization per age class is constant, and thus utilization is a model parameter. Assumptions about utilization levels made by Buddhakulsomsiri et al. (2006) are identical to the assumptions made by Redmer (2005). In addition, Buddhakulsomsiri et al. (2006) explain that decreasing utilization might follow from a dependent use pattern: "Given that the various vehicles are available to provide the same service or perform the same function, it is the newer ones that are generally preferred." The explanation proposed by Buddhakulsomsiri et al. (2006) coincides with our thoughts about possible reasons for decreasing utilization. Eventually, by minimizing the total costs of purchasing, selling, owning, and operating equipment units over a finite planning horizon Buddhakulsomsiri et al. (2006) provide a fleet specific and cost minimal buy, operate, and sell policy.

2.1.5 Models addressing problems related to equipment replacement in fleets

Problems related to equipment replacement in fleets are analyzed by Khasnabis et al. (2003), Davenport et al. (2005) and Rees et al. (1982). Khasnabis et al. (2003) assume that future demand for fleet services and the expected costs of replacement, rehabilitation and remanufacturing are known. The authors show that the optimal capital allocation for the dual purpose of purchasing new equipment units and rebuilding existing ones within the constraint of a fixed budget can be obtained with linear programming. For a fleet of cutaway passenger vans Davenport et al. (2005) create a fleet condition forecast model. By using a regression model they find out that the parameters equipment age, total mileage, miles per year on unpaved roads, lift equipment, and percentage of population older than age 65 are the best equipment condition predictors. Rees et al. (1982) make a replacement demand forecast by simulating the steady process of deterioration and equipment break down within a Markov type network.

2.2 MODELS USED IN PRACTICE

The literature review shows that equipment replacement problems occurring in vehicle fleets are addressed in many ways. While examining published and proposed methodologies the question arises as to which policy or policies are actually used by agencies in daily business? To answer this question we conducted a telephone survey of a selection of U.S. state DOTs. We ask them what kind of replacement methodology they are currently using. In most cases replacement is organized by replacement priority rankings which use a limited selection of ranking criteria (see Table 1). A conversation with the Division Chief of Washington State Department of Transportation (WDOT) reveals that WDOT started with a LCCA model similar to that used by a commercial long distance fleet transportation company when they initially set up their replacement methodology. LCCA models assume that annualized maintenance and operating costs do not decrease while equipment is growing older. According to the Division Chief, this requirement is not fulfilled by WDOT fleet, and consequently, WDOT stopped using LCCA. The thoughts which were made at WDOT coincide with our concerns about applying LCCA to the ODOT fleet which shows decreasing utilization over equipment age. However, we are surprised that still two DOTs stated that they plan on conducting LCCA in the near future in order to improve their vehicle replacement. The fact that 89% of the DOTs admitted that the selection of criteria used in replacement decisions originates from experience and not from scientific models puts the substantial amount of research made in this area into question. Although it seems like replacement decisions made by most interviewed agencies have no scientific basis, quantitative data driven models are used. The models used in practice generate replacement priority rankings based on a set of certain ranking criteria that differs for different state DOTs. Typically, a model will utilize a measure computed as a ratio relative to a fixed standard for some given ranking criteria. For example if mileage is used as a ranking criteria, then a measure computed for a single asset may be the asset mileage divided by a fixed mileage standard. The result of our telephone survey indicates that the criteria mileage/hours and time in service are used by 89% of those contacted. Only 56% use repair cost limits in their models which might be contradictory to the results from Chee (1975) and particularly Love et al. (1982) et al. In accordance with the literature only a minority of the contacted agencies regards operating costs as a suitable parameter to support replacement decisions.

Table 1, Results from telephone survey conducted between 02/12/08 and 02/26/08

Department of Transportation	Managed Fleet	Replacement Priority Ranking Criteria: Mileage/Hours	Time in Service	Operating Cost	Repair Cost	Acquisition Cost	Physical Assessment	Experience based Policy	Plan to apply LCCA in the near Future
Alabama DOT	All equipment	x	x					x	
California DOT	All equipment	x	x		x				
Florida DOT	All equipment	x	x				x	x	x
Illinois DOT	Heavy trucks	x			x		x	x	
Michigan DOT	Heavy trucks		x				x	x	
Oregon DOT	All equipment	x	x	x	x	x		x	
Texas DOT	All equipment	x	x		x	x		x	
Virginia DOT	All equipment	x	x		x			x	x
Washington State DOT	All equipment	x	x					x	
Portion of DOTs using criteria		89%	89%	11%	56%	22%	33%	89%	22%

2.3 IMPACT OF THIS RESEARCH

We conducted both a review of published literature, and a telephone survey among U.S. state DOTs to assess the state-of-the-art in equipment replacement modeling. Recommended methods in literature rely heavily on assumptions made about the fleet and on conditions under which the fleet is operated. Two studies address explicitly a case of decreasing utilization over equipment age as seen with many assets in state DOTs. The authors point out that the assumptions of the standard economic life model do not hold for a fleet with decreasing utilization. The telephone survey reveals that state DOTs are familiar with age dependent use patterns and that state DOTs manage replacement decisions with simple models. In these models equipment units are typically ranked based on measures computed relative to standards for various criteria. The standards and criteria that are a part of most ranking systems currently in use by state DOTs are not quantitatively justified but instead are experience based. For fleets showing decreasing utilization over equipment age, it is not possible to identify a dominant replacement strategy.

The literature review and telephone survey show that there is a discrepancy between theory and practice. While published literature offers a multitude of methodologies to derive cost efficient replacement decisions –LCCA is the most prominent amongst them – a selection of nine U.S. DOTs do not apply any of these methodologies. Instead, in practice simple asset rankings based on different measures incorporating fixed standards which are mostly experience based are utilized. The contribution of this research is the testing and selection of simple and cost minimizing replacement prioritization measures, and justifying its effectiveness relative to other measures with data and scientific reasoning.

3 MATERIALS AND METHODS

In this research we are looking for the most cost efficient equipment replacement prioritization measure for the ODOT fleet. Based on the literature review and telephone survey no single prioritization measure or replacement methodology stands out as the most cost efficient. Simulation is used in this research to evaluate different prioritization measures. Simulation is utilized so that the actual operating characteristics of the ODOT fleet could be represented as accurately as possible. A major component of a simulation study is data preparation and analysis.

3.1 DATA PREPARATION

ODOT Fleet Services provides management of a fleet consisting of approximately 4,930 (as of 2008) pieces of active equipment. This equipment includes a variety of small and large trucks, cars, as well as heavy machinery such as graders, bulldozers, and many types of tractors. The different types of equipment in the ODOT fleet are organized into equipment classes. In this research a selection of larger and more expensive equipment classes was simulated. Historical cost and usage data for individual equipment units in these classes was obtained. Preparation and analysis of this data included adjusting historical costs for inflation, analyzing correlation in the data, and fitting probability distributions to mileage and different costs.

3.1.1 Organization of historical fleet data in matrix format

The historical data available from ODOT included acquisition cost, and annual records of mileage, repair costs, fixed costs, and operating costs. For most equipment, mileage, repair costs, fixed costs, and operating costs were recorded for the time period of July 1994 to June 2002. For each equipment unit active in ODOT fleet between July 1994 and June 2002 acquisition costs are also provided even if these costs were incurred before July 1994. The equipment for which data was available, were of various ages.

For each equipment class, records were organized so that mileage, repair costs, fixed costs and operating costs are separated from each other into subsets. Within each subset, the data is placed into columns for different equipment ages to generate a data matrix.

In Table 2 a drafted data matrix is presented for a hypothetical example equipment class. Each row in this data matrix contains records from a different unit of equipment and each column in the matrix represents a specific data item for a specific equipment age. In this research, we assume that the maximum age reached by ODOT fleet equipment is 25 years. This assumption is important as it dictates the maximum equipment age in the simulation (cf. section 3.2). Therefore, we reserve 25 columns for each type of cost and usage data.

Table 2, Example for a n-by-p data matrix[3] showing the organization scheme of historical fleet data (R = recorded parameter value, EQ_x = equipment unit x, M_x = mileage traveled by equipment aged x, RC_x/FC_x/OC_x = repair cost/fix cost/operating cost generated by equipment aged x, AC = acquisition cost)

	M_01	M_02	…	M_12	M_13	…	M_24	M_25	RC_01	RC_02	…	RC_12	RC_13	…	RC_24	RC_25	FC_01	FC_02	…	FC_12	FC_13	…	FC_24	FC_25	OC_01	OC_02	…	OC_12	OC_13	…	OC_24	OC_25	AC
EQ_A	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R
EQ_B	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R	R	…	R	-	…	-	-	R
EQ_C	-	R	…	R	R	…	-	-	-	R	…	R	R	…	-	-	-	R	…	R	R	…	-	-	-	R	…	R	R	…	-	-	R
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
EQ_X	-	-	…	R	R	…	-	-	-	-	…	R	R	…	-	-	-	-	…	R	R	…	-	-	-	-	…	R	R	…	-	-	R
EQ_Y	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	R
EQ_Z	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	-	-	…	-	R	…	R	-	R

In the left part of the data matrix, records of traveled mileage are organized into columns M_01 through M_25. Six actual time series of mileage coming from equipment units A, B, C, X, Y, and Z are shaded grey. Similarly, recorded time series of repair costs, fix costs and operating costs as well as the acquisition cost are shaded grey. This makes it easy to recognize that equipment unit A was tracked while it aged from one through twelve years and equipment unit Z was tracked while it aged from thirteen to 24. Equipment is sorted from equipment unit A to equipment unit Z such that the earliest records in equipment life are at the top of the matrix and the latest records in equipment life are at the matrix's bottom. The example data matrix in Table 2 shows recorded time series of data by equipment age. Records of data for a particular piece of equipment can start at any equipment age, and is only limited by the physical life time of observed units. Recorded data come from equipment units of various ages (compare EQ_A to EQ_Z). A data time series in the data matrix stops either when an individual equipment unit is eliminated from the fleet or when the process of data recording is stopped – in our example after twelve years.[4] It is important

[3] *n-by-p* matrix stands for "number of rows"-by-"number of columns" matrix. In this case n represents the total number of observed equipment units and p equals to 101 representing the quadruple of annual parameters recorded over 25 equipment ages each and acquisition cost.

[4] It is also possible that both elimination and stopping the process of recording occur at the same point in time.

to recognize that equipment units which are added to the observed equipment class while recording continues appear automatically at the top of the data matrix because recording starts when a units' age is one.

3.1.2 Selection of five ODOT equipment classes

The five largest equipment classes in the ODOT fleet were selected for this research. The main reason is that more data are available so that the true operating characteristics of the equipment class are better represented. The actual equipment classes considered are listed in Table 3.

Table 3, ODOT equipment classes considered in this study

Equipment Class	Description	Fleet Size
Sedan	Sedans	~ 180 units
Pickup	¾ ton pickups with two wheels rear drive	~ 270 units
Truck LT	Light trucks with two wheels rear drive	~ 270 units
Truck MED	Medium trucks with two wheels rear drive and diesel engine	~ 170 units
Truck HVY	Heavy diesel trucks	~ 370 units

One of the largest equipment classes in ODOT's fleet is Truck HVY with 226 members. A smaller equipment class considered in this research is Sedan with 108 members.[5] The number of available parameter records per year decreases as the equipment grows older. The decrease starts at different ages depending on the equipment class. For equipment class Truck HVY there are at least 25 records for each age of age 20 and younger, but only four or less records for trucks of age 20 and older. For Sedans the number of records decreases to 23 through age eleven, and for ages twelve and older there are less than nine records per equipment age.

The number of data records per age depends on the length of class specific service life as well as on the total size of an equipment class. A larger equipment class shows more records per age than a smaller one. An equipment class with characteristically long service life has more records per age, particularly more records at higher ages, than an equipment class with generally short service life. The average service life of heavy diesel trucks is longer than the average service life of sedans. Moreover, the class Truck HVY is

[5] The exact number of records over equipment age for each analyzed equipment class can be found in the appendix in Table 31.

nominally larger than equipment class Sedan. This explains why Truck HVY provides sufficient data through the age of 20 whereas Sedan does so only until the age of eleven.

For the simulation a "*sufficient* " number of data records per equipment age is needed. A sufficient amount of records is judged based on visual analyses to be 20 or more records per equipment age. Visual analysis indicates that records do not provide reasonable results in terms of statistical mean and standard deviation once the number of records per year slips below the limit of 20[6]. Columns of mileage, repair costs, fixed costs, and operating costs that do not contain enough data are cleared in the data matrix.

3.1.3 Adjustment for price inflation

A data matrix generated from data provided by ODOT contains historical acquisition cost and time series of mileage, repair costs, fixed costs, and operating costs (see Table 2). Annual costs and mileage data were recorded by ODOT for individual equipment units primarily between July 1, 1994 and June 30, 2002. In order to make the costs comparable, it is necessary to adjust them for inflation. All cost data was adjusted to reflect costs prevalent during the ODOT accounting year July 1, 2001 to June 30, 2002 (2001/2002) (i.e. the last year of recording).

Table 4, Consumer price indexes used to adjust historical costs

Cost Type	**Used CPI**
Repair cost	U.S. city average; Motor vehicle maintenance and repair; NSA[7]; 1947-2008
Fix cost	U.S. city average; Motor vehicle insurance; NSA; 1947-2008
Operating cost	U.S. city average; Motor fuel; NSA; 1935-2008
Acquisition cost	U.S. city average; New vehicles; NSA; 1947-2008

Four different consumer price indexes (CPI) published by the U.S. Department of Labor were used to adjust costs (see Table 4). CPIs are given as monthly data. The average of twelve monthly CPIs (July through June) was used as the CPI for a corresponding ODOT accounting year. Price inflators were computed by dividing the 2001/2002-CPI by CPIs from earlier periods. The results are presented in Table 5.

[6] Visual analyses consider trends in the mean and standard deviation of mileage and costs over equipment age. We could find that clearly visible trends terminate once there are provided less than 20 data records per equipment age.

[7] NSA = not seasonally adjusted

Table 5, Price inflators used to normalize costs generated by ODOT equipment to the price level of ODOT accounting year 2001/2002 (extract[8])

Accounting Year	Price Inflator for Repair Cost	Price Inflator for Fix Cost	Price Inflator for Operating Cost	Price Inflator for Acquisition Cost
2001/2002	1	1	1	1
2000/2001	1.0367	1.0699	0.8546	0.9898
1999/2000	1.0725	1.0943	0.9659	0.9880
1998/1999	1.1024	1.1002	1.2404	0.9852
1997/1998	1.1351	1.0980	1.1373	0.9817
1996/1997	1.1633	1.1239	1.0607	0.9765
1995/1996	1.1982	1.1668	1.1102	0.9917
1994/1995	1.2294	1.2172	1.1193	1.0104
…	…	…	…	…

Historical costs which were recorded during a certain accounting year are adjusted by multiplication with a corresponding price inflator. In the following sections we assume that data in Table 2 have been adjusted for inflation as described.

3.1.4 Correlation analysis

In this section, correlation between the five data types mileage, repair costs, fixed costs, operating costs, and acquisition costs is investigated. Spearman's rank correlation is utilized as the measures of correlation. Spearman's rank correlation compared to Pearson product-moment correlation has the advantage that rank correlation is distribution independent. Pearson correlation measures the strength of the linear relationship between two variables. However, if two variables do not have the same probability distribution, they are unlikely to be linearly related. Under these circumstances, Spearman's rank correlation coefficient is more appropriate.

[8] For the full table see Table 33 in the appendix.

Table 6, Upper triangular p-by-p matrix containing the pair wise Spearman's rank correlation coefficient ρ between each pair of columns of Table 2 (denoted as full correlation matrix)

	M_01	M_02	…	M_12	M_13	…	M_24	M_25	RC_01	RC_02	…	RC_12	RC_13	…	RC_24	RC_25	FC_01	FC_02	…	FC_12	FC_13	…	FC_24	FC_25	OC_01	OC_02	…	OC_12	OC_13	…	OC_24	OC_25	AC
M_01	1	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
M_02		1	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…			1	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
M_12				1	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
M_13					1	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…						1	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
M_24							1	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
M_25								1	-	-	…	-	-	…	-	-	-	-	…	-	-	…	-	-	-	-	…	-	-	…	-	-	-
RC_01									1	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
RC_02										1	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…											1	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
RC_12												1	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
RC_13													1	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…														1	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
RC_24															1	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
RC_25																1	-	-	…	-	-	…	-	-	-	-	…	-	-	…	-	-	-
FC_01																	1	ρ	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
FC_02																		1	…	ρ	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…																			1	…	…	…	…	…	…	…	…	…	…	…	…	…	…
FC_12																				1	ρ	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
FC_13																					1	…	ρ	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
…																						1	…	…	…	…	…	…	…	…	…	…	…
FC_24																							1	-	ρ	ρ	…	ρ	ρ	…	ρ	-	ρ
FC_25																								1	-	-	…	-	-	…	-	-	-
OC_01																									1	ρ	…	ρ	ρ	…	ρ	-	ρ
OC_02																										1	…	ρ	ρ	…	ρ	-	ρ
…																											1	…	…	…	…	…	…
OC_12																												1	ρ	…	ρ	-	ρ
OC_13																													1	…	ρ	-	ρ
…																														1	…	…	…
OC_24																															1	-	ρ
OC_25																																1	-
AC																																	1

The data matrix (Table 2) serves as input for correlation analysis which was conducted with MATLAB R2008a[9]. MATLAB offers a function that returns a p-by-p matrix containing the pair wise Spearman's rank

[9] MATLAB is a numerical computing environment and programming language.

correlation coefficient between each pair of columns in the n-by-p input matrix. The function computes a pair wise rank correlation coefficient $\rho(i, j)$ between each pair of columns i and j and only considers rows with no missing values in column i and j. For example, when MATLAB computes the rank correlation coefficient between the columns M_12 and M_13 in Table 2, the computation only considers rows of EQ_C, EQ_X and other rows which have no missing values. For instance, the row of EQ_B is not included in the calculation because there is no mileage record for equipment unit B provided when it was thirteen years old.

The general form of the results of correlation analysis with Matlab is shown in Table 6. Table 6 shows an upper triangular 101-by-101 matrix containing pair wise Spearman's rank correlation coefficients between each pair of columns in the input matrix (Table 2). For example, coefficient $\rho(M\_12, M\_13)$ in Table 6 represents the value of Spearman's rank correlation between mileage of equipment aged twelve and mileage of equipment aged thirteen. The diagonal of the triangular matrix is filled with ones because each column in Table 2 is perfectly correlated with itself.

The last step of correlation analysis is manipulation of Table 6 so that results can be used easily as input for random variate generation. The upper triangular p-by-p matrix in Table 6 is referred to as the *full* correlation matrix because this matrix contains all correlation coefficients which are computed by MATLAB. The *reduced* correlation matrix (see Table 7) contains correlation coefficients utilized in the simulation. In order to generate the reduced correlation matrix the following steps were executed in order:

1. Cells which have no content are filled with "-".

2. Correlation coefficients considered redundant are eliminated. The remaining correlation coefficients are:

    a. Correlation between columns of the same data type and recorded at consecutive equipment ages.
    Example: $\rho(M\_12, M\_13)$

    b. Correlation between columns of different data types recorded at identical equipment ages.
    Example: $\rho(M\_12, RC\_12)$

c. Correlation between acquisition cost and any other data type.
   Example: $\rho(M\_12, AC)$

3. We regard correlation between columns as insignificant if $\rho \leq 0.5$. Correlation coefficients meeting this requirement are replaced by "-".

4. Depending on the equipment class, data records stop earlier or later over equipment age. Recall that the equipment class Sedan provides records through the age of eleven whereas sufficient data for Truck HVY exists through the age of 20. As a result, some cells in the full correlation matrix will be left empty because correlation coefficients could not be computed. If these empty cells have not been cleared either in step 2 or step 3, they need to be filled with reasonable values.

   a. Table 6 shows that MATLAB provided no result for $\rho(M\_24, M\_25)$. Remember that the data does not have records for equipment aged 25. Moreover, $\rho(M\_24, M\_25)$ was not deleted in either step 2 or step 3. In order to make a suitable forecast for $\rho(M\_24, M\_25)$, the arithmetic mean of the available correlation coefficients is used:

   $$\rho(M\_24, M\_25) = \frac{\sum_{t=1}^{23} \rho(M\_t, M\_t+1)}{23}.$$

   Forecasts are calculated analogously for $\rho(RC\_24, RC\_25)$ and $\rho(OC\_24, OC\_25)$.

   b. For correlation between different data types the formula looks very similar:

   $$\rho(FC\_25, AC) = \frac{\sum_{t=1}^{24} \rho(FC\_t, AC)}{24},$$

   and is also used for $\rho(M\_25, RC\_25)$, $\rho(M\_25, OC\_25)$, $\rho(RC\_25, OC\_25)$.

5. The empty cells on the matrix diagonal are filled with ones so that each column in Table 2 is perfectly correlated with itself.

These five steps of matrix manipulation applied to a full correlation matrix generated by MATLAB yields the reduced correlation matrix which contains all correlation patterns between recorded data utilized in the simulation. Some further explanation is necessary to justify the described manipulation steps:

Table 7, Reduced correlation matrix containing selected rank correlation coefficients from Table 6

	M_01	**M_02**	**…**	**M_12**	**M_13**	**…**	**M_24**	**M_25**	**RC_01**	**RC_02**	**…**	**RC_12**	**RC_13**	**…**	**RC_24**	**RC_25**	**FC_01**	**FC_02**	**…**	**FC_12**	**FC_13**	**…**	**FC_24**	**FC_25**	**OC_01**	**OC_02**	**…**	**OC_12**	**OC_13**	**…**	**OC_24**	**OC_25**	**AC**
M_01	1	ρ							ρ																ρ								
M_02		1	…							ρ																ρ							
…			1	…							…																…						
M_12				1	ρ							ρ																ρ					
M_13					1	…							ρ																ρ				
…						1	…							…																…			
M_24							1	ρ							ρ																ρ		
M_25								1								ρ																ρ	
RC_01									1	ρ															ρ								
RC_02										1	…															ρ							
…											1	…															…						
RC_12												1	ρ															ρ					
RC_13													1	…															ρ				
…														1	…															…			
RC_24															1	ρ															ρ		
RC_25																1																ρ	
FC_01																	1																ρ
FC_02																		1															ρ
…																			1														…
FC_12																				1													ρ
FC_13																					1												ρ
…																						1											…
FC_24																							1										ρ
FC_25																								1									ρ
OC_01																									1	ρ							
OC_02																										1	…						
…																											1	…					
OC_12																												1	ρ				
OC_13																													1	…			
…																														1	…		
OC_24																															1	ρ	
OC_25																																1	
AC																																	1

Step 2: The reduction of the full correlation matrix to those correlations described in step 2 was found to be sufficient. Two sets of random variates were generated. One based on a full correlation matrix and

another based on the corresponding reduced correlation matrix[11]. Correlation analysis of the generated sets of random variates yields roughly identical full correlation matrixes for both sets of random variates. Thus, it appears that the reduction in step 2 deletes redundant information.

Step 3: The requirement to determine a pair of parameters as uncorrelated is $\rho \leq 0.5$. The limit of 0.5 was chosen arbitrarily. It has been our experience that low correlation ($\rho \leq 0.5$) has no major impact on the outcome of random variate generation in this application. Moreover, it is our motivation to simplify the correlation matrix. Under these circumstances 0.5 is considered as a reasonable threshold.

Step 4: Empty cells in the correlation matrix are filled with the arithmetic mean of correlation coefficients computed for the same pair of data types. For equipment of higher age there are fairly constant correlation levels over equipment age. This empirical result is independent of the equipment class and the data type.

Reduced correlation matrixes generated for the five equipment classes generate average correlation coefficients as presented in Table 8.

Table 8, Average Spearman's rank correlation coefficients found in historical ODOT fleet data

	Mileage	**Repair Cost**	**Fix Cost**	**Operating Cost**	**Acquisition Cost**
Mileage	0.6	0.45	0	0.75	0
Repair Cost		0.45	0	0	0
Fix Cost			0	0	0.7
Operating Cost				0.6	0
Acquisition Cost					0

3.1.5 Distribution fitting

The last step of data preparation is to find the best fit probability distribution for each data type for each equipment age. The fitting is done separately for each of the five analyzed ODOT equipment classes. The Kolmogorov-Smirnov goodness of fit test (K-S test) which ranks fitted distributions based on the largest vertical distance between an empirical distribution function of the data and the cumulative distribution

[11] The exact procedure of random variate generation incorporating a 101-by-101 upper triangular rank correlation matrix is described in section 3.2.

function of the hypothesized distribution is used. Crystal Ball 7.3[12] was used for distribution fitting. This software conducts K-S tests and identifies the best fit from fourteen continuous reference distributions[13].

Recall the n-by-p data matrix (see Table 2) where each row represents a unit of equipment and each column is labeled with one of the four annually recorded data types recorded for a certain equipment age. This matrix is the input data for distribution fitting. Values in each column represent an empirical distribution of a distinct data type at a distinct equipment age. A continuous statistical distribution was fit to each column.

Table 9, Result of Kolmogorov-Smirnov goodness of fit test applied on historical fleet data presented in Table 2

Sample:	**M_01**	**M_02**	**…**	**M_12**	**M_13**	**…**	**M_24**	**M_25**	**RC_01**	**RC_02**	**…**	**RC_12**	**RC_13**	**…**	**RC_24**	**RC_25**	**FC_01**	**FC_02**	**…**	**FC_12**	**FC_13**	**…**	**FC_24**	**FC_25**	**OC_01**	**OC_02**	**…**	**OC_12**	**OC_13**	**…**	**OC_24**	**OC_25**	**AC**
Best fit:	BetaPERT	Gamma	…	Normal	Beta	…	Beta	Lognormal	Beta	Gamma	…	Weibull	Weibull	…	Lognormal	Lognormal	Student's t	Logistic	…	BetaPERT	Logistic	…	Beta	Lognormal	Beta	Max Extreme	…	Beta	Lognormal	…	Beta	Lognormal	Logistic
K-S statistic of best fit:	0.0483	0.0445	…	0.0516	0.0616	…	0.0708		0.0679	0.1399	…	0.2111	0.2289	…	0.2537		0.1705	0.2037	…	0.0445	0.0483	…	0.0516		0.0616	0.0708	…	0.0679	0.1399	…	0.2111		0.1273

Crystal Ball assesses the fit of fourteen continuous distributions to the empirical distribution functions generated from the data. This is performed for every single column of the data matrix for each equipment class. The goodness of fit is quantified by the Kolmogorov-Smirnov statistic (K-S statistic) which is the largest vertical distance between empirical distribution function of the sample and cumulative distribution function of the reference distribution. Among all fourteen fitted reference distribution functions the one which yields the lowest K-S statistic is identified as the best fit. For instance, distribution fitting on data from the example fleet (Table 2) shows that a continuous statistical distribution of type BetaPERT is the best fit for miles traveled at equipment age one (column M_01 in Table 2). The value of

[12] Crystal Ball software is a spreadsheet-based software suite for predictive modeling, forecasting, Monte Carlo simulation and optimization.

[13] Crystal Ball conducts the Kolmogorov-Smirnov goodness of fit test with statistical continuous probability distributions of type Normal, Triangular, Lognormal, Uniform, Exponential, Weibull, Beta, BetaPERT, Gamma, Logistic, Pareto, Max Extreme, Min Extreme, and Student's t.

the corresponding K-S statistic is computed as 0.0483. Table 9 shows the results of probability distribution fitting of data from the example fleet. Beside the information presented in Table 9, Crystal Ball also computes estimates of the parameters of each best fit distribution. Distribution types and distribution parameters characterize the best fit distributions.

Since there are no data records for equipment aged 25 it is impossible to conduct a goodness of fit test for mileage or any of the annual cost parameters. When no data exists for a particular age for an equipment class, it is assumed that the data follow a lognormal distributed.[14] Lognormal distributions are characterized by two parameters: mean and standard deviation. The required distribution parameters are generated by graphical analysis of prior means and standard deviations.

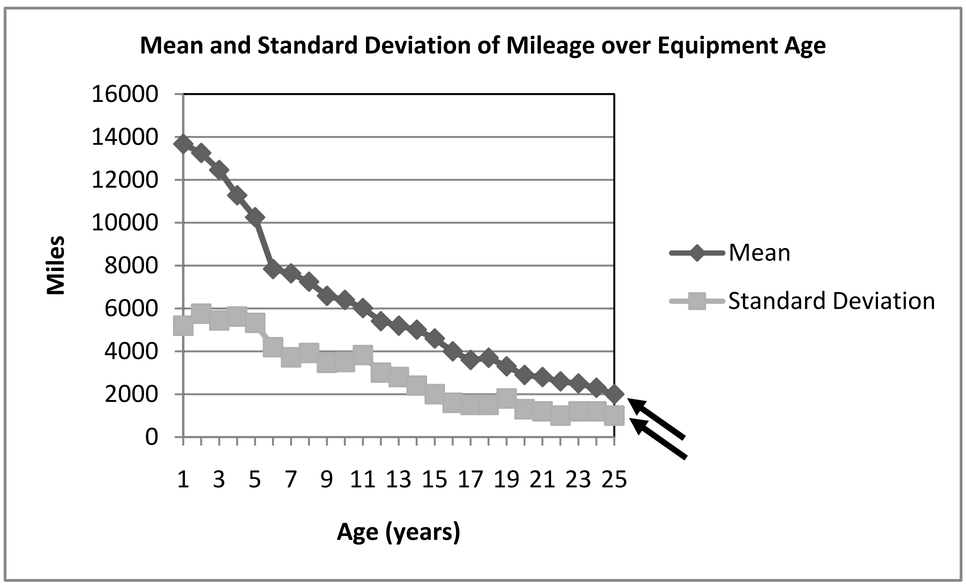


Figure 1, Mean and standard deviation of mileage including forecast (see arrows) over equipment age

The process of distribution parameter forecasting is explained using the example of mileage. In order to analyze graphically the mean and standard deviation of mileage over time consider the columns M_01 through M_24 in Table 2. The mean and standard deviation for each column are computed, i.e. for

---

[14] The use of lognormal distributions has several advantages. Its parameters are straightforward to estimate, and can represent any coefficient of variation. Random variates generated from a lognormal distribution are by definition nonnegative which is necessary for random variates representing mileage, repair costs, fixed costs or operating costs. Finally, the third and fourth standardized moments, skewness and kurtosis, will most likely have only minor effects on the outcome of our simulation.

annually traveled mileage over equipment age. Computed values are plotted in Figure 1. A forecast for mean and standard deviation of mileage at equipment age 25 is made by continuing the chart smoothly by hand. In Figure 1 forecasts are indicated by arrows. Estimated values for mean and standard deviation are taken from the graph and used as parameters for the lognormal distribution of M_25 in Table 9. This procedure is repeated in order to specify lognormal distributions of repair cost, fixed costs, and operating costs for equipment age 25.[16]

Although this forecasting method seems unconventional it is more appropriate and easier to apply than forecasting methods like single and double moving average or exponential smoothing. In particular, the analyzed equipment class Sedan provides historical data only for equipment ages one through eleven. In this case, a fourteen years forecast has to be made for the mean and standard deviation of mileage and for each of the three cost categories. Over such a long period, moving average and exponential smoothing forecasts do not produce reasonable outcomes. Single moving average and single exponential smoothing forecasts result in a constant value which does not reflect clear negative trends. Double moving average and double exponential smoothing methods are likely to forecast values below zero for higher equipment ages. Recall that ODOT equipment shows decreasing trends in utilization, i.e. in annual mileage. Thus, double moving average and double exponential smoothing forecasts tend to continue the negative trend without turning convex when equipment grows older to avoid negative values for annual mileage and costs.

In this section we have determined best fit continuous distributions for four data types for 25 different equipment ages, and also for acquisition cost. 101 distributions have been fit, which will be used in the simulation. As a last step some probability distributions' ranges are truncated so that no negative values are possible. Although truncation of the range does affect the distribution's mean and variance the induced perturbation is very small.

3.2 SIMULATION

Historical data provided by ODOT included mileage, repair costs, fixed costs, and operating costs which were recorded annually over eight consecutive years for each member of ODOT's fleet. Furthermore,

---

[16] Means derived from historical ODOT fleet data and mean forecasts for mileage, repair costs, fixed costs, and operating costs for all five equipment classes are visualized in graphs (see in the appendix Figure 9, Figure 10, Figure 11, and Figure 12)

acquisition costs for each equipment unit were recorded. In section 3.1 five ODOT equipment classes were selected for simulation. For these five equipment classes, historical records have been organized into data matrixes. A single data matrix contains 101 columns. Historical cost records in the data matrixes have been adjusted for inflation so that prices are normalized to the price level of the ODOT accounting year 2001/2002. Data matrices have been analyzed for correlation and correlation coefficients have been organized into upper triangular correlation matrixes. Finally, for each column in the data matrixes the best fit continuous probability distribution function has been determined and truncated if necessary.

The objective of this research is to evaluate simple replacement prioritization measures that can be used to rank equipment for replacement. The tested prioritization measures can be considered as factors that can be changed in the simulation. The simulation does not explicitly model a specific budget constraint. Instead a budget constraint is implicitly established as the number of pieces of equipment that can be replaced at each replacement epoch. This quantity of replacements per replacement epoch is independent of the tested prioritization strategy and can be treated as a factor in the simulation. The following describes how the data which was prepared in sections 3.1.1 through 3.1.5 is used in the simulation.

3.2.1 Generation of random variates from fitted distributions

In section 3.1.5 we have identified the best fit continuous distributions for mileage, inflation adjusted acquisition costs as well as inflation adjusted repair costs, fixed costs, and operating costs over 25 equipment ages (see Table 9). These distributions have been truncated so that generated random variates will always be positive. Moreover, in section 3.1.4 we have determined the existing rank correlation between data records (see Table 7).

Table 10, Parameters generated randomly from fitted probability distribution functions (Table 9) (G = generated parameter)

	M_01	**M_02**	**…**	**M_12**	**M_13**	**…**	**M_24**	**M_25**	**RC_01**	**RC_02**	**…**	**RC_12**	**RC_13**	**…**	**RC_24**	**RC_25**	**FC_01**	**FC_02**	**…**	**FC_12**	**FC_13**	**…**	**FC_24**	**FC_25**	**OC_01**	**OC_02**	**…**	**OC_12**	**OC_13**	**…**	**OC_24**	**OC_25**	**AC**
EQ_000	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G
EQ_002	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
EQ_998	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G
EQ_999	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G

The process of random variate generation will be described using the equipment class from the example fleet introduced in section 3.1.1. We generate 101 random variates simultaneously from the 101 distributions presented in Table 9. Such a set of 101 random variates fills a row in Table 10 and contains annual mileage and annual costs adjusted for inflation. A row in Table 10 describes a randomly generated unit of equipment and its mileage and costs over 25 years. 1000 rows, i.e. 1000 equipment units, are generated and then stored in one table (see Table 10). Although the data in each row are generated by a random number generator, the generated equipment units represent characteristic mileage and cost patterns from the original equipment class of the example fleet. This is because the actual fleet data was fit to the probability distributions and correlation has been considered.

Crystal Ball was used to generate 1000 rows of equipment data from fitted distribution functions with and also without consideration of correlation. Thus, two different tables are generated for an equipment class. In order to conduct a superficial verification that the generation of random variates was successful, sample means and standard deviations from the historical data were compared to the means and standard deviations from the generated samples. For each of the 101 parameters we compute the percent deviation between the means of the original data and generated sample (Equation 1) as well as the percent deviation between the standard deviations of the original and generated sample (Equation 2).

$$\Delta_{Mean}^{\%} = \left(\frac{\overline{y}_{original\ sample}}{\overline{y}_{generated\ sample}} - 1 \right)$$

Equation 1

$$\Delta_{StdDev}^{\%} = \left(\frac{S_{original\ sample}}{S_{generated\ sample}} - 1 \right)$$

Equation 2

101 values for $\Delta_{Mean}^{\%}$ and 101 values for $\Delta_{StdDev}^{\%}$ are computed based on columns in Table 2 and Table 10, and then $\sigma(\Delta_{Mean}^{\%})$ and $\sigma(\Delta_{StdDev}^{\%})$ were computed. $\sigma(\Delta_{Mean}^{\%})$ near zero percent and $\sigma(\Delta_{StdDev}^{\%})$ between five and fifteen percent were observed depending on the equipment class. Results for all five analyzed equipment classes can be found in the appendix in Table 32.

3.2.2 Simulation of equipment replacement

We have generated two tables of 1000 hypothetical equipment units (Table 10). The simulation uses the data in these tables as a supply of new equipment to replace equipment already in the fleet. Before the simulation starts four simulation parameters are specified (see Table 11).

Table 11, Simulation parameters

Simulation Parameter	Values and Explanation
Interval of replacement	Replacement is accomplished every other year and starts in year zero.
Duration	We simulate equipment replacement over 500 consecutive years.
Length of warm up period	The simulation warms up 300 years before another 500 years (Duration) follow. Performance measures are computed based on records made during the 500 years period after warm up period.
Number of replication	We produce five replicates of each simulation configuration.

The simulation is organized in a three dimensional simulation matrix. A partial, cross sectional view on this matrix is shown in Table 12. The first dimension of the simulation matrix is time. Table 12 shows that the header of the cross sectional view is labeled with ascending year dates. The simulation moves along this axis as it advances in time. The second dimension of the simulation matrix is equipment. The first column of Table 12 contains equipment unit identifications. The simulation moves down this axis as new equipment units are added to the fleet. Each equipment unit which is added to the fleet forms an additional row and extends the simulation matrix at the bottom. The third dimension of the simulation matrix is for the different types of data for each equipment unit. This dimension is not visible in Table 12 but it can be easily described as additional tables being arranged behind Table 12. These tables arranged along the third axis are identical to Table 12 except for the fact that each table contains a different type of data (data entries are symbolized by capital Gs in Table 12). In other words, when moving along the third axis of the simulation matrix we see the first table containing annual mileage data, the second table containing annual repair cost data, etc. Beyond mileage, repair costs, fixed costs, and operating costs other data like equipment age and acquisition cost, and accumulated mileage, and variables for internal use like the current replication number are also organized along the third dimension of the simulation matrix. The three dimensional matrix allows us to store data which is either for a specific equipment unit at a specific age (e.g. annual mileage), or for a specific equipment unit without further reference to age (e.g. acquisition cost), or only to the simulation as a whole (e.g. replication number).

Table 12, Partial cross sectional view on simulation matrix used to organize the process of simulation (G = generated parameter pulled from Table 10 according to equipment unit and equipment age, EQ_xxxx = equipment unit xxxx, Year_xxxx = xxxxth year of simulation)

	…	Year_0332	Year_0333	Year_0334	Year_0335	Year_0336	Year_0337	Year_0338	Year_0339	Year_0340	Year_0341	Year_0342	Year_0343	Year_0344	Year_0345	Year_0346	Year_0347	Year_0348	Year_0349	Year_0350	Year_0351	Year_0352	Year_0353	Year_0354	Year_0355	Year_0356	Year_0357	Year_0358	Year_0359	Year_0360	Year_0361	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
EQ_0266	…	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G													…
EQ_0593	..			G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G													..
EQ_0887	…			G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G													…
EQ_0627	…			G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G											…
EQ_0508	…					G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G											…
EQ_0645	…					G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G											…
EQ_0714	…					G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G									…
EQ_0908	…							G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G									…
EQ_0809	…							G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G									…
EQ_0052	…							G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G							…
EQ_0524	…									G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G							…
EQ_032	…									G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G							…
EQ_0523	…									G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G					…
EQ_0848	…											G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G					…
EQ_0137	…											G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G					…
EQ_0283	…											G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G			…
EQ_0222	…													G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G			…
EQ_0908	…													G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G			…
EQ_0292	…													G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0761	…															G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0692	…															G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0581	…															G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0461	…																	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0860	…																	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0558	…																	G	G	G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0284	…																			G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0319	…																			G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0398	…																			G	G	G	G	G	G	G	G	G	G	G	G	…
EQ_0584	…																					G	G	G	G	G	G	G	G	G	G	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…

The simulation starts in year zero. An initial selection of equipment units is chosen randomly from Table 10. Data records for mileage, repair costs, fixed costs, operating costs, and acquisition cost are copied into the matrix. Equipment replacement occurs every other year as is the case with the ODOT fleet. Thus, after year zero the first replacement happens in year two which is not visualized in Table 12 since the view does not include column Year_0002.

The replacement quantity for regular replacements is determined by the fleet size simulated and the average replacement age. The inter arrival time of new equipment is deterministic: Replacement is accomplished every other year. Thus, the arrival process is a stationary ergodic process. Every time replacement occurs, replacement candidates are selected based on a replacement priority ranking. The actual distribution of time spent in the system, i.e. the distribution of equipment age at replacement, depends on the applied replacement prioritization measure. It is assumed that after a warm up period a stable distribution for time spent in the system establishes, and thus, a stationary system emerges.[18] The time between replacements is determined, fleet size is set to a fixed value, and equipment age is limited to 25 years.

In a queuing process, let $\frac{1}{\lambda}$ be the mean time between the arrivals of two consecutive units, N be the mean number of units in the system, and T be the mean time spent by a unit in the system. Little (1961) shows, if the three means are finite and the corresponding stochastic processes strictly stationary, and, if the arrival process is ergodic with nonzero mean, then $N = \lambda T$ (Little's Law). In this research N is given by the size of the simulated fleet, λ is interpreted as the average replacement quantity per year, and T is the average replacement age.

The simulation algorithm selects every other year 2λ equipment units according to the generated replacement priority ranking and replaces them with new ones. For demonstration purpose we apply prioritization measure "replace oldest first" on the analyzed equipment class of the example fleet. Thus, Table 12 shows the simulation of a 25 units counting fleet with average replacement age set to be approximately 16.6 years and applied replacement prioritization measure "replace oldest first". The amount of equipment units which are due to replacement every other year is computed with Little's Law and yields three (see Equation 3).

---

[18] Simulation results indicate that this assumption is correct. For a given replacement quantity per year λ and a given fleet size N the average replacement age T corresponds to calculations using Little's Law independently of the applied replacement prioritization measure.

$$\Leftrightarrow 2\frac{N}{T} = 2\lambda$$
$$\Leftrightarrow 2\frac{25}{16.6} = 3.0120$$
$$\Rightarrow 2\lambda \approx 3$$

Equation 3

At the beginning of each run the simulation “warms up” for 300 years. This allows the simulation to establish – if possible – a steady state system. After the warm up period of 300 years has passed, recording of performance measures starts. Table 12 shows the state of the simulation between simulated years 332 and 361. The cross sectional view shows that at the beginning of every even year three random equipment units drawn randomly from Table 10 are added. Moreover, three equipment units are eliminated from the simulated fleet as soon as one unit has finished its 18th year of life and the other two their 16th year of life. The dark gray shaded column of year 351 shows that the simulated fleet has exactly 25 active fleet members at an arbitrarily chosen point of time.

In the example (Table 12) replacement prioritization measure “replace oldest first” guaranties replacement of individual equipment units at average replacement age 16.6 years. The chosen prioritization measure makes sure that variance of replacement age is zero. However, replacement age of individual equipment units can vary depending on the applied replacement prioritization measure. Although we set the average replacement age to be either 8.3 or 16.6 years, it is possible that individual equipment units reach the age of 25. As mentioned in section 3.1.1 the maximum age for equipment considered in this research is set to be 25 years. As soon as an equipment unit reaches the age of 25, the simulation algorithm assigns a very high replacement priority to this unit so that it will be replaced before other younger equipment. Thus, each equipment unit is replaced at latest after its 25th year of life. The simulation tracks these replacements due to reaching maximum age.

The process of randomly choosing equipment units from Table 10 is accomplished using a random number generator. This random number generator produces a random number X with $X \in [0,1]$. X is multiplied with 999 and the simulation algorithm picks that equipment unit from Table 10 whose identification coincides with the generated random number between 0 and 999. Each simulation for which data results are collected is replicated five times. The random number generator uses five different seeds for these five replicates. Arbitrarily the seeds are set equal to the replication number of the simulation run. This approach is applied without exception on every simulation run. Thus, unnecessary variance between different simulation runs caused by using different seeds is avoided.

3.2.3 Replacement prioritization measures

The centerpiece of the simulation is the ability to test different replacement prioritization measures in order to investigate their impact on fleet costs. Results from a telephone survey (see section 2.2) indicate that fleets managed by U.S. state DOTs typically make replacement decisions based on simple rankings of replacement candidates. Findings from the literature review, telephone survey and discussions within the research team resulted in the set of prioritization measures presented in Table 14. Further, these ten prioritization measures have three characteristics in common which are necessary requirements according to the objectives of this research:

1. The replacement prioritization measures are simple.
2. The replacement prioritization measures rely solely on annual or accumulated fleet data for usage, repair costs, fixed costs, operating costs, and acquisition cost.
3. The prior characteristics imply that replacement prioritization measures one through ten can be implemented by ODOT instantaneously without any major changes to their existing equipment management software.

Each of the tested prioritization measures provides a unique rule to rank active members of the simulated fleet. The top ranked equipment unit has the highest priority to be replaced and the lowest ranked equipment unit has the lowest replacement priority. The prioritization measures are computed using data stored in the simulation matrix (see section 3.2.2). Each time replacement will occur the simulation algorithm computes the rankings.

Table 13, Age standards and use standards

Equipment Class	Age Standard (years)	Use Standard (miles)
Sedan	8	100000
Pickup	8	125000
Truck LT	8	125000
Truck MED	12	250000
Truck HVY	15	300000

Table 14, Replacement prioritization measures

No.	Replacement Prioritization Measure	Explanation	Cat.
1	Replace random first	Active equipment units are ranked by a random number generator[21]. "Replace random first" is considered as a reference methodology.	Random
2	Replace oldest first	Active equipment units are ranked based on the time they have spent as active fleet members.	Accumulative
3	Replace highest life usage first	Active equipment units are ranked based on the accumulated miles they have traveled during the time spent as active fleet members.	Accumulative
4	Replace highest $\left(\text{life repair cost} + \text{life operating cost}\right)$ first	Active equipment units are ranked based on the accumulated repair and operating cost they have produced during the time spent as active fleet members.	Accumulative
5	Replace highest (life total cost) $\left(\text{life repair cost} + \text{life operating cost} + \text{life fix cost}\right)$ first	Active equipment units are ranked based on the accumulated total cost they have produced during the time spent as active fleet members.	Accumulative
6	Replace highest (modified ODOT model) $\left(\frac{\text{age}}{\text{age std}} + \frac{\text{life usage}}{\text{use std}}\right)$ first	Active equipment units are ranked based on the presented ratio which is denoted as the modified ODOT model. For age and use standard (=std) refer to Table 13.	Accumulative divided by standard
7	Replace highest (current ODOT model) $\left(\frac{\text{age}}{\text{age std}} + \frac{\text{life usage}}{\text{use std}} + \frac{\text{life total cost}}{\text{acquisition cost}}\right)$ first	Active equipment units are ranked based on the presented ratio which is currently used by ODOT Fleet Services. For age and use standard (=std) refer to Table 13.	Accumulative divided by standard
8	Replace highest (repair cost delta) $\left(\text{repair cost}(t) \text{ - repair cost}(t-1)\right)$ first	Active equipment units are ranked based on the highest positive difference between repair cost produced during the current year and the preceding.	Discrepancy
9	Replace highest (total cost delta) $\left(\text{total cost}(t) \text{ - total cost}(t-1)\right)$ first	Active equipment units are ranked based on the highest positive difference between total cost produced during the current year and the preceding year.	Discrepancy
10	Replace highest (operating and repair cost per mile) $\left(\frac{\text{life repair cost} + \text{life operating cost}}{\text{life usage}}\right)$ first	Active equipment units are ranked based on the highest accumulated operating and repair cost per mile computed for the time units have spent as active fleet members.	Cost per mile

[21] The seed used by this random number generator is determined in the same way as the seed determined for the random number generator described at the end of section 3.2.2. But in this case the seed is shifted linearly by 50.

Prioritization measures six and seven require an age standard and use standard which depend on equipment class. For each of the five analyzed equipment classes current age and use standards are shown in Table 13. Values in Table 13 represent recommendations from ODOT Fleet Services. Specific values for age and use standards reflect the age and accumulated mileage expected to be provided by an average unit of equipment. Denominators in replacement prioritization measures six and seven are implemented for normalization purposes. They transform values given in years, miles, or monetary units to dimensionless ratios. Necessary replacement of an equipment unit is indicated when these ratios are valued above one. Little use of an equipment unit is indicated in case the ratios are valued below one. Hence, normalization facilitates creating replacement priority rankings which consider a multitude of parameters of different character. Further, the value of a ratio computed according to prioritization measure six or seven depends on the value of the standards. Thus, standards which are incorporated as denominators of those ratios have an important impact on the prioritization measure's ranking outcome.

In the right most column of Table 14, prioritization measures one through ten are assigned to categories. Five different categories are introduced. Prioritization measure one provides random equipment replacement. This measure serves as a reference. Prioritization measures two through five are categorized as accumulative. Computed values rise monotonically as units of equipment grow older. Similarly, prioritization measures six and seven define monotonically rising ranking criteria as units of equipment grow older, but as the name of the category suggests values are divided by standards. Replacement prioritization measures eight and nine provide replacement based on discrepancies which are computed for the most recent biennium. Prioritization measure ten is categorized as cost per mile and aims at representing a measure for efficiency.[22] The least efficient equipment unit, i.e. the equipment unit which is most expensive per unit of usage, is replaced first. Fixed costs are ignored because they are not usage-linked, and thus, cannot account for an inefficient mode of operation. Furthermore, prioritization measure ten is based on accumulated rather than annual data in order to create a measure which is more robust against annual fluctuations.

---

[22] Odeck et al. (1996) analyzes the efficiency of individual trucks and assesses efficiency based on the ratio between inputs and outputs.

3.2.4 Performance measures

After a warm up period of 300 years the simulation algorithm records different data during the following 500 years of simulation. Based on this data performance measures are computed. Performance measures considered in this study are summarized in Table 15.

Table 15, Performance measures based on data recorded during a single simulation run

Performance Measure	Explanation
Total cost per mile	The average value for repair cost + fix cost + operating cost per traveled mile
Total cost per equipment year	The average value for total cost (see previous row), traveled miles, and equipment age per equipment year. In other words, values are given for a single average unit of equipment during a single average year.
Miles per equipment year	
Equipment age per equipment year	
Percent overaged units	The percentage of equipment units replaced during a simulation run that has reached the age of 25 years.

3.2.5 Experimental Design

Ten replacement prioritization measures and other factors whose impact on costs shall be tested have been introduced. In order to perform simulation runs with different treatment combinations most efficiently statistical design of experiments has been utilized. According to Montgomery (2005) statistical design of experiments ensures that generated data, analyzed by statistical methods, will allow valid and objective conclusions.

The experiment in this research uses primarily a 2^3 x 10 full factorial design testing 80 different treatment combinations, i.e. 80 simulation configurations. Factors and corresponding treatment levels are summarized in Table 16. A treatment combination that is simulated is replicated five times, so that 400 simulation runs are necessary for a single equipment class. For the five analyzed equipment classes, 2000 simulation runs were completed. Randomization of run order is not necessary because simulations results are not affected by run order. For each replication of a particular experiment seeds used for random number generation are changed. However, the same replication for different experiments use identical seeds. A single simulation run simulates equipment replacement and fleet utilization over 500 years. The response variable of primary interest is total cost per mile (see Table 15).

Table 16, Factors and treatment levels

	Factors			
	Correlation	**Average Replacement Age**	**Fleet Size**	**Prioritization Measure**
Treatment Levels	Reduced correlation	~ 8.3 years	25	Measure 1
				Measure 2
				Measure 3
				Measure 4
				Measure 5
	No correlation	~ 16.6 years	50	Measure 6
				Measure 7
				Measure 8
				Measure 9
				Measure 10

4 RESULTS

A 2^3 x 10 full factorial experiment was conducted for each equipment class. Analysis of variance (ANOVA) was conducted on the experimental results to identify factors that influence the response variable, i.e. total cost per mile, significantly. The results obtained from the 2^3 x 10 full factorial provided reasons for simplification of the experiment to a 2^1 x 10 full factorial design. ANOVA was applied to this experiment to determine which remaining factors have a statistically significant effect on total cost per mile. Interaction plots and multiple range tests are conducted in order to investigate if replacement prioritization measures can be sorted into homogeneous groups which produce statistically identical results. Residual plots are generated to check ANOVA assumptions. Details of the results analysis will be presented next.

4.1 2^3 X 10 FACTORIAL DESIGN OF EXPERIMENT

The simulation provided five sets of data – one for each of the analyzed equipment classes. These data are analyzed separately and formally tested for differences in the response (cost per mile). For each equipment class a multifactor analysis of variance was conducted to determine which factors have a statistically significant effect on the total cost per mile. Results are presented in ANOVA tables.[23]

4.1.1 Analysis of variance

ANOVA tables decompose the variability of the response variable due to the four factors (see Table 16). The contribution of each factor is measured having removed the effects of all other factors. The F-test provides P-values which test the statistical significance of each of the factors. In case a P-value is less than 0.05, the corresponding factor has a statistically significant effect on total cost per mile at a 95.0 percent confidence level. In other words, a statistically significant difference in the response is indicated at a significance level of five percent.

Figure 2 shows the interaction effect between factors replacement prioritization measure and correlation for equipment class Truck HVY. Two lines drawn on the graph represent the two levels of correlation. They connect the means of total cost per mile for the ten replacement prioritization measures. If there was absolutely no interaction, these lines would be parallel. In this case, the different shapes of lines

---

[23] ANOVA tables for Truck HVY (see Table 34), Truck MED (see Table 36), Truck LT (see Table 38), Pickup (see Table 40), and Sedan (see Table 42) are provided in the appendix.

indicate interaction, i.e. the difference in total cost per mile between the levels of factor correlation is not the same at all levels of factor prioritization measure. Results from the F-test show a significant interaction effect (see Table 34).

The main effects of factors correlation and prioritization measure can also be investigated with Figure 2. If the level of correlation had absolutely no effect on total cost per mile, both lines in Figure 2 would be drawn above each other. In other words, the response variable would be independent from correlation level. Further, if the choice of prioritization measure had no effect on total cost per mile, lines would be horizontal. Thus, the response variable would be the same no matter which prioritization measure would be chosen.

The interaction plot in Figure 2 suggests significant main effects of factors prioritization measure and correlation. The assumption is supported by the F-test. The P-values for main effects of factors prioritization measure and correlation are below 0.05 (see Table 34). Thus, with at least 95 percent certainty choice of prioritization measure as well as consideration of correlation has an effect on total cost per mile.

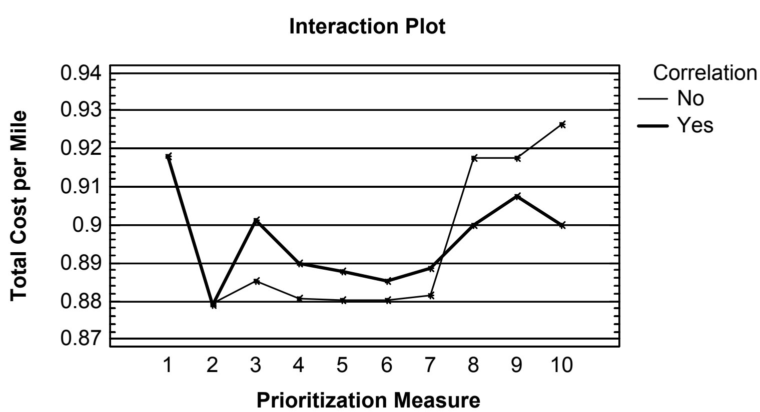


Figure 2, Truck HVY: Significant effect of correlation and prioritization measure on total cost per mile

Figure 3 presents the interaction effect between factors prioritization measure and average replacement age. Again, lines representing the two levels of average replacement age fall far apart. A statistically significant main effect of factor average replacement age is proven in the F-test. The corresponding P-value (see Table 34) is below 0.05. The choice of average replacement age level has an effect on the response variable at a confidence level of 95 percent.

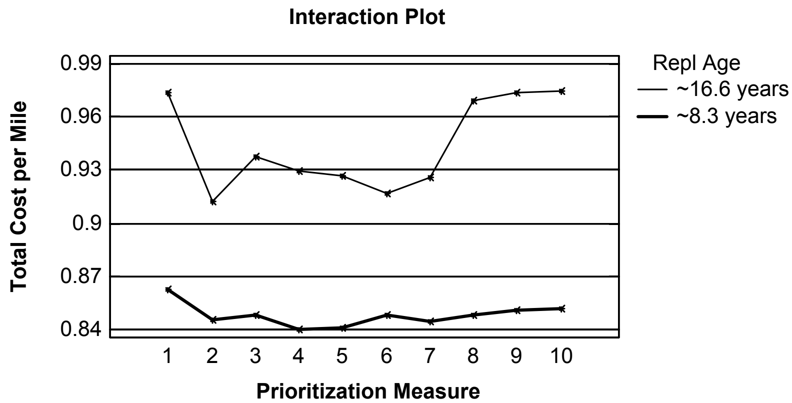


Figure 3, Truck HVY: Significant effect of average replacement age on total cost per mile

In contrast to lines drawn in Figure 2 and Figure 3, the two lines representing two levels of fleet size in Figure 4 are drawn practically above each other. Thus, the level of total cost per mile does not depend on fleet size. The P-value for the main effect of factor fleet size is 0.7793. In other words, given that fleet size has no effect on the response variable, i.e. given the null hypothesis is true, the probability that the two lines fall at least as far apart as shown in Figure 4 as a result of the underlying variance is 77.93 percent. Thus, fleet size does not have a statistically significant effect on total cost per mile at the 95 percent confidence level.

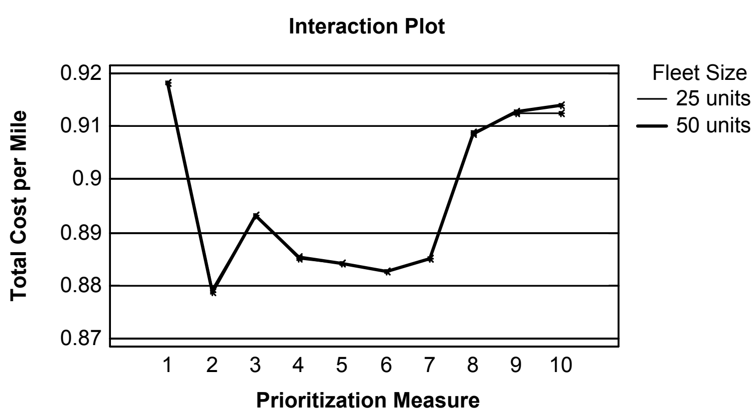


Figure 4, Truck HVY: Insignificant effect of fleet size on total cost per mile

P-values indicate very similar results across equipment classes. The P-values for main effects are identical across equipment classes with one exception. ANOVA results for equipment class Truck MED indicate that fleet size does have a statistically significant effect. The P-Value of the main effect of factor fleet size is 0.0472 and thus below the significance level 0.05 (see Table 36). However, the corresponding interaction plot in Figure 5 reveals that the effect of fleet size on total cost per mile is marginal in economical terms. The statistical significance of fleet size in equipment class Truck MED is therefore neglected.

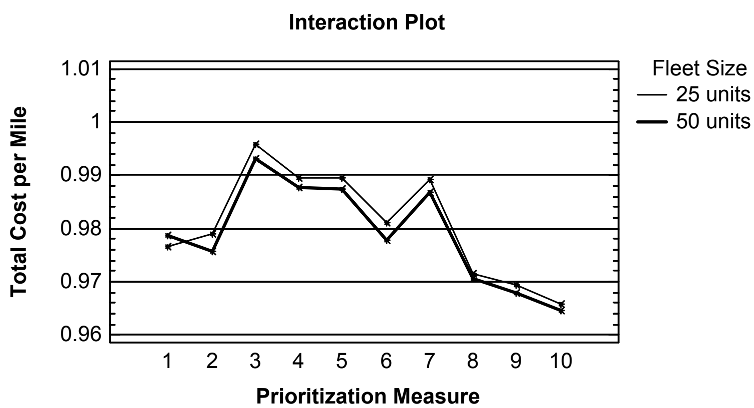


Figure 5, Truck MED: Statistically significant but still marginal effect of fleet size on total cost per mile

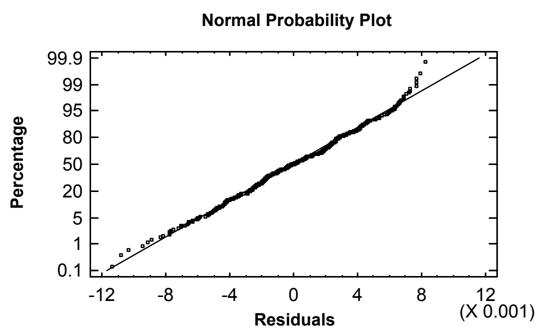
ANOVA results are summarized in Table 17. Analysis of variance for total cost per mile in the 2^3 x 10 full factorial design of experiment yields very similar results for all five equipment classes. Factors replacement prioritization measure, correlation, and average replacement age do have a statistically significant effect on total cost per mile and factor fleet size does not.

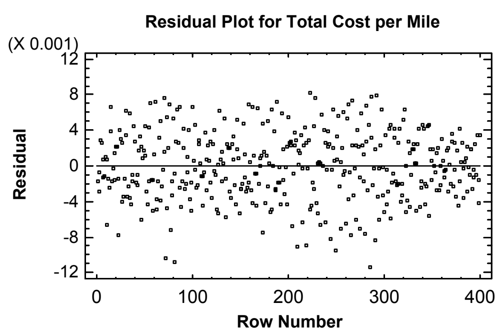
Table 17, ANOVA results for main effects in all five equipment classes

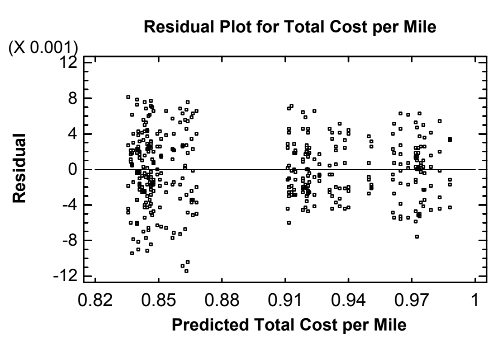
Factor	Significance at the 95 Percent Confidence Level
Replacement prioritization measure	Significant
Correlation	Significant
Average replacement age	Significant
Fleet size	Not significant

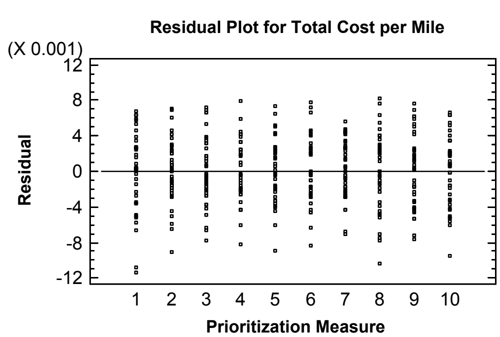
4.1.2 Model adequacy checking

Table 18, Truck HVY: Model adequacy checking for total cost per mile (2^3 x 10 factorial design)

<table>
<tr><td>
</td><td>If the underlying error distribution is normal the normal probability plot resembles a straight line.

The general impression from examining this normal probability plot of residuals is that the error distribution is nearly perfectly normal.</td></tr>
<tr><td>
</td><td>This plot shows the residuals versus row number in the file. Any pattern other than a random scatter could indicate some serial correlation or time dependence in the data.

This plot of residuals versus row number provides no reason to suspect violation of the independence or constant variance assumptions.</td></tr>
<tr><td>
</td><td>This plot shows the residuals versus predicted levels of total cost per mile. This plot is useful for detecting heteroscedasticity, in which the variance of total cost per mile changes together with the mean. If the points make a general funnel-shaped pattern, it indicates a type of heteroscedasticity.

This plot of residuals versus predicted total cost per mile provides no reason to suspect violation of the independence or constant variance assumptions.</td></tr>
<tr><td>
</td><td>This plot shows the residuals versus levels of prioritization measure. The residuals are equal to the observed values of total cost per mile minus the mean total cost per mile for the group from which they come. The independence assumption implies that residuals should be unrelated to any other variable including the predicted response.

This plot of residuals versus prioritization measure does not provide any reason to suspect violation of the independence or constant variance assumptions.</td></tr>
</table>

Before the results from the presented analysis of variance can be adopted, the adequacy of the underlying model has to be checked. According to Montgomery (2005) the analysis of variance procedure is an exact test of the hypothesis of no differences in treatment means only if certain assumptions are satisfied. Specifically, these assumptions are that the observations are adequately described by an effects model (see Montgomery (2005)) and that the errors are normally and independently distributed with mean zero and constant variance. The primary diagnostic tool is residual analysis. The residual of an observation is defined as the difference between the observation and the corresponding treatment mean. The most important residual plots for total cost per mile are presented and commented in Table 18.

Assumptions about normality, constant variance and independence of total cost per mile residuals are verified in Table 18 for equipment class Truck HVY. Residual analyses conducted for the other four equipment classes lead to similar results. Model adequacy can be confirmed for each of the analyzed equipment classes. Thus, ANOVA results for all five equipment classes summarized in Table 17 are valid.

4.2 2^1 X 10 FACTORIAL DESIGN OF EXPERIMENT

In the previous section it is shown that fleet size does not have a statistically significant effect on response variable total cost per mile. Therefore, factor fleet size is not considered in the following analyses. Moreover, simulation results from data sets that originate from simulation runs considering no correlation are not used. The reasoning is that correlation exists in historical fleet data provided by ODOT. If it turned out that correlation was not a significant factor, future simulations could be simplified by not analyzing and simulating correlation. The resulting 2^1 x 10 full factorial design of experiment includes two factors: average replacement age (budget) and replacement prioritization measure.

4.2.1 Analysis of variance

A multifactor analysis of variance for total cost per mile organized in a 2^1 x 10 factorial design of experiment does not provide new results for any of the analyzed equipment classes. In all five equipment classes main effects of factors average replacement age and replacement prioritization measure are statistically significant at a 95.0 percent confidence level.[24]

---

[24] ANOVA tables for Truck HVY (see Table 35), Truck MED (see Table 37), Truck LT (see Table 39), Pickup (see Table 41), and Sedan (see Table 43) are provided in the appendix.

4.2.2 Interaction plots

In section 4.1.1 interaction plots have been used to detect significant main effects and to interpret results from F-tests. In this section further results are suggested from the simulation by analyzing interaction plots.

In Table 19 five interaction plots are presented. For each of the analyzed equipment classes the means of total cost per mile are plotted for two levels of average replacement age versus applied replacement prioritization measure. Graphs show that average replacement age 16.6 years does lead to higher total cost per mile than average replacement age 8.3 years. There is no prioritization measure that visibly dominates at both levels of replacement age and in all five equipment classes. However, patterns do repeat. Interaction plots for equipment classes Pickup and Sedan are similar to Truck HVY at average replacement age 16.3 years. For equipment classes Truck MED and Truck LT the plots seem similar for average replacement age 16.6 years. Prioritization measure one (replace randomly) provides rather bad results, i.e. high total cost per mile.

Table 20 shows selected interaction plots generated for equipment class Truck HVY. Total cost per mile is correlated with other performance measures. A Low level of total cost per mile occurs with a high level of total cost per equipment year, a high level of traveled miles per equipment year, a low level of average equipment age, and a low fraction of equipment units that reach the age of 25 years. A visual analysis reveals that prioritization measure two (replace oldest first) performs best in this environment.

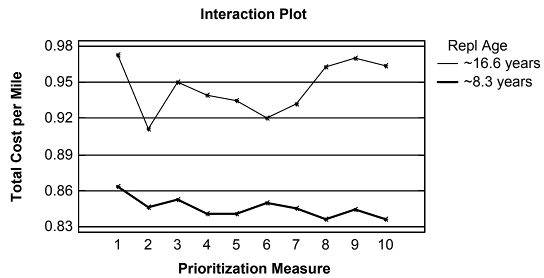
Correlations identified for Truck HVY are not confirmed by simulation results for equipment class Truck MED. Table 21 shows the same types of graphs as Table 20 but for equipment class Truck MED. In this case a low level of total cost per mile occurs with a low level of total cost per equipment year, a low level of mileage per equipment year, a high level of average equipment age, and a high fraction of equipment units that reach the maximum age. Prioritization measure ten (replace lowest efficiency first) is dominant.

Visual analysis of data from the remaining equipment classes reveals that Sedan and Pickup resemble equipment class Truck HVY and that Truck LT shows characteristic of both Truck HVY und Truck MED. [25]

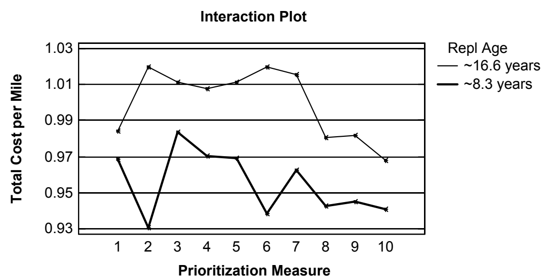
---

[25] Comparisons of selected interaction plots for equipment classes Truck LT (see Table 44), Pickup (see Table 45), and Sedan (see Table 46) are presented in the appendix.

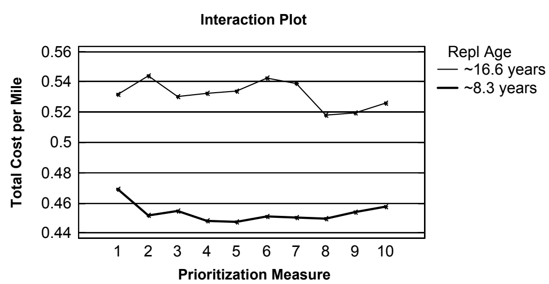
Table 19, Means of total cost per mile versus prioritization measure and replacement age in comparison

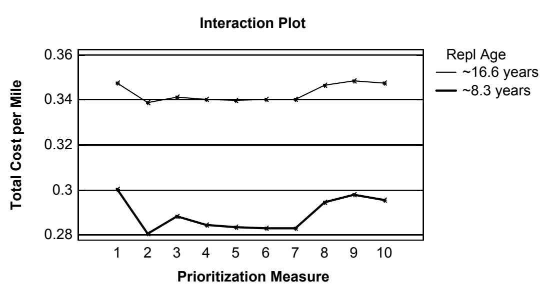
<table>
<tr><td>
</td><td>Truck HVY

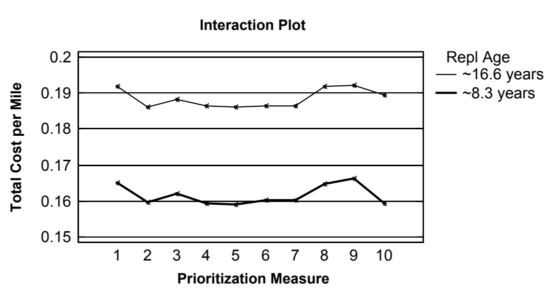
For average replacement age 16.6 years prioritization measure two (replace oldest first) provides best results.

For average replacement age 16.6 years the choice of prioritization measure does have an economically substantial effect on total cost per mile of six Dollar cents per mile at maximum.</td></tr>
<tr><td>
</td><td>Truck MED

For average replacement age 16.6 years prioritization measure one (replace randomly) produces surprisingly low total cost per mile compared to other prioritization measures.

For average replacement age 16.6 years prioritization measures eight through ten provide best results which is contrary to Truck HVY.</td></tr>
<tr><td>
</td><td>Truck LT

For average replacement age 8.3 years choice of prioritization measure does not make a big difference in total cost per mile (prioritization measure one not considered).</td></tr>
<tr><td>
</td><td>Pickup

For average replacement age 8.3 years prioritization measure (replace oldest first) provides best results.</td></tr>
<tr><td>
</td><td>Sedan

For average replacement age 8.3 years choice of prioritization measure affects total cost per mile by less than one cent at maximum.</td></tr>
</table>

Table 20, Truck HVY: Comparison of selected interaction plots

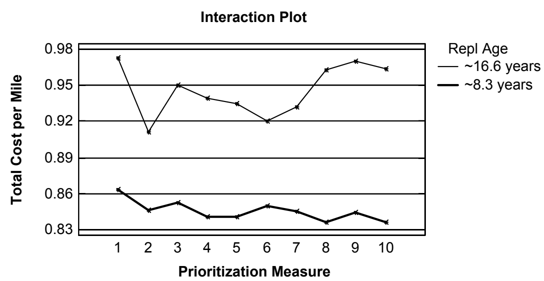
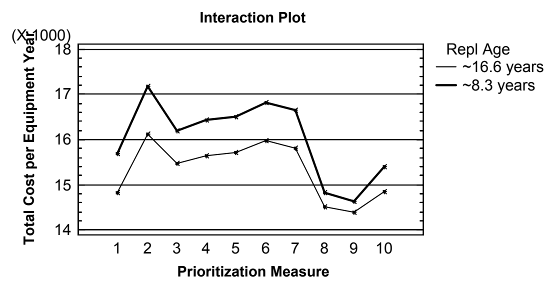
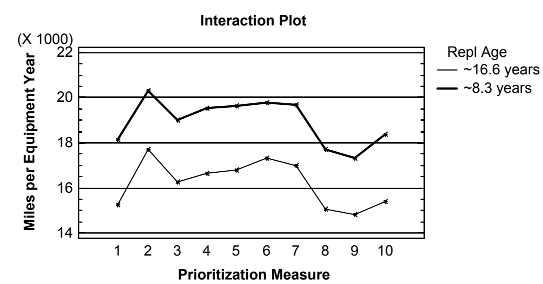
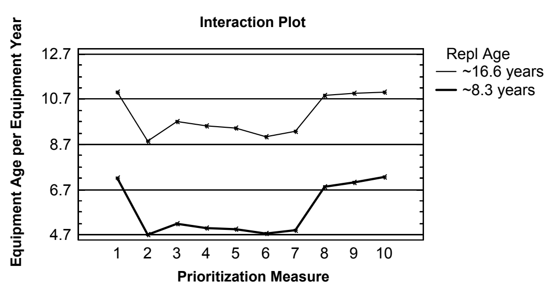
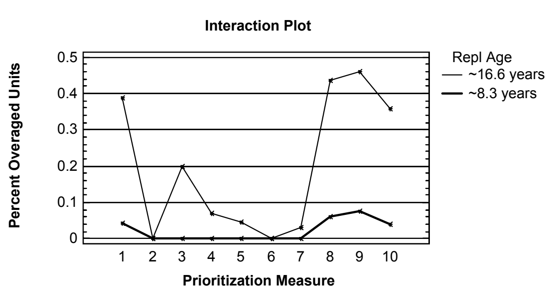
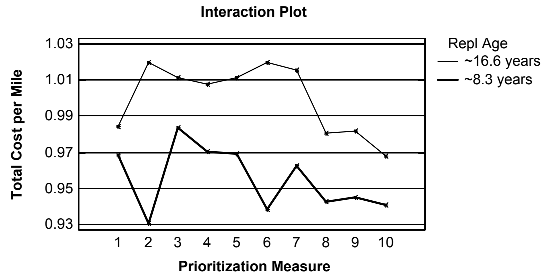
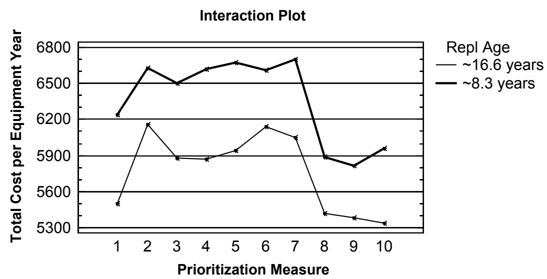
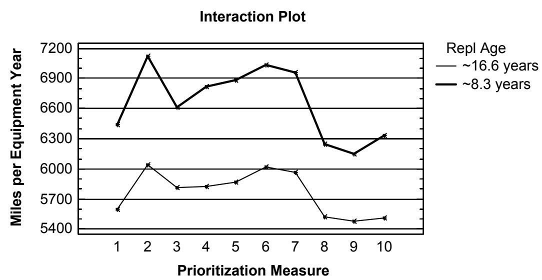
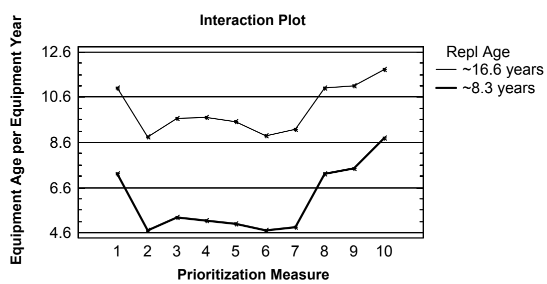
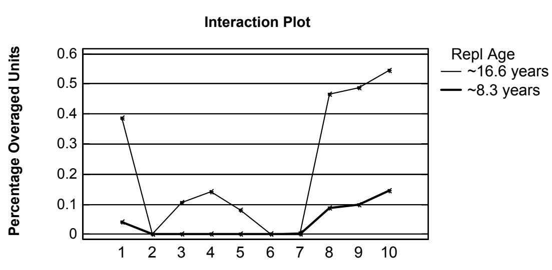
	This graph shows average total cost spent per traveled mile versus prioritization measure and is identical to the first top graph in Table 19. For average replacement age 16.6 years prioritization measure two (replace oldest first) and prioritization measure six (modified ODOT model) produce the lowest total cost per mile.
	This graph shows average total cost spent per equipment unit and per year versus prioritization measure. For prioritization measures two and six total costs per equipment year are at their highest level.
	This graph shows average mileage traveled per equipment unit and per year versus prioritization measure. For prioritization measures two and six traveled miles per equipment year are at their highest level.
	This graph shows average equipment age versus prioritization measure. For prioritization measures two and six the average age of equipment is at its lowest level.
	This graph shows the average fraction of equipment units reaching the age of 25 from all equipment units that have been part of the fleet during the simulation versus prioritization measure. The lowest fractions of equipment units reaching the age of 25 for average replacement age 16.6 years appear with prioritization measures two and six.

Table 21, Truck MED: Comparison of selected interaction plots

	For average replacement age 16.6 years prioritization measure ten (replace lowest efficiency first) produces the lowest total cost per mile.
	For prioritization measure ten total costs per equipment year are at a lower level.
	For prioritization measure ten traveled miles per equipment year are at a lower level.
	For prioritization measure ten the average age of equipment is at its highest level.
	The highest fraction of equipment units reaching the age of 25 for average replacement age 16.6 years appears with prioritization measure ten.

4.2.3 Multiple comparison tests

In section 4.2.1 we have shown that the choice of prioritization measure does have a statistically significant effect on total cost per mile. Further, results for total cost per mile do depend on the analyzed equipment class (see Table 19). Finally, visual evaluation does not allow the identification of a single prioritization measure that dominates in each equipment class and at both levels of average replacement age.

In this section a multiple comparison test is applied to determine which means of total cost per mile are significantly different from which others. The multiple comparison test is applied for total cost per mile by prioritization measure separately for average replacement age 8.3 years and 16.6 years because of significant interaction of the two factors. The method used to discriminate among the total cost per mile means is Tukey's honestly significant difference (HSD) procedure which is also known as Tukey’s test.[27] With this method, there is a risk of α of calling one or more pairs of means significantly different when their actual difference equals zero. In other words, means of total costs per mile connected by a line in graphs in Table 19 are regarded as a set. We compare all pairs of means in a set and the null hypotheses that we test are $H_0 : \mu_i = \mu_j$ for all $i \neq j$ with $i, j \in \{\text{Measure } 1, \text{Measure } 2, \ldots, \text{Measure } 10\}$. Tukey’s multiple comparison procedure for testing these null hypotheses ensures that the overall significance level per analyzed set is exactly α.

The studentized range statistic is $q_{\alpha=0.05}(p, f) = 4.61$ with $p = 10$ sample means per analyzed set and $f = 90$ degrees of freedom associated with the MS_E. The underlying MS_E is taken from the ANOVA table which was generated for total cost per mile in the 2^1 x 10 factorial design of experiment for the corresponding equipment class.[28] With $n = 10$ representing the sample size of total cost per mile, Tukey’s test declares two means significantly different if the absolute value of their sample differences exceeds

$$T_\alpha = q_\alpha(p, f)\sqrt{\frac{MS_E}{n}}.$$

---

[27] See Tukey (1953).

[28] ANOVA tables for Truck HVY (see Table 35), Truck MED (see Table 37), Truck LT (see Table 39), Pickup (see Table 41), and Sedan (see Table 43) are provided in the appendix.

Table 22, Truck HVY & Truck MED: Tukey's test for total cost per mile by prioritization measure

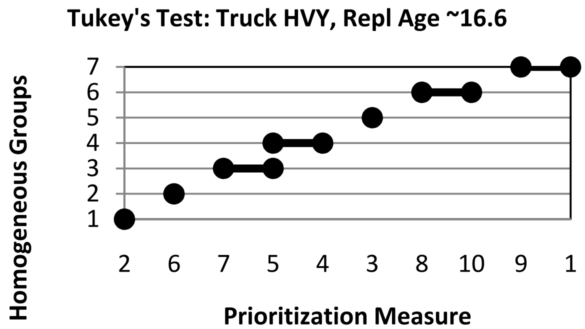
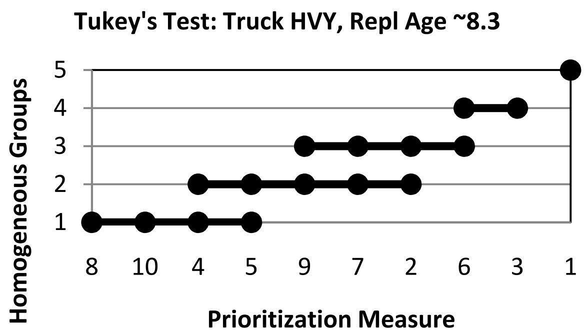
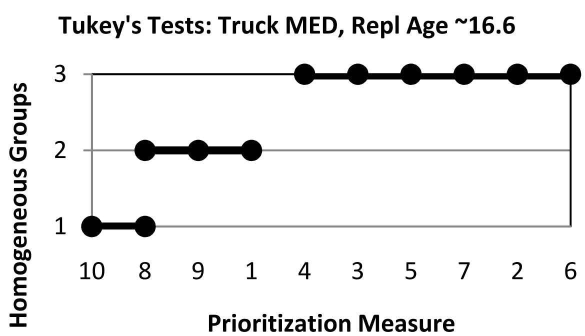
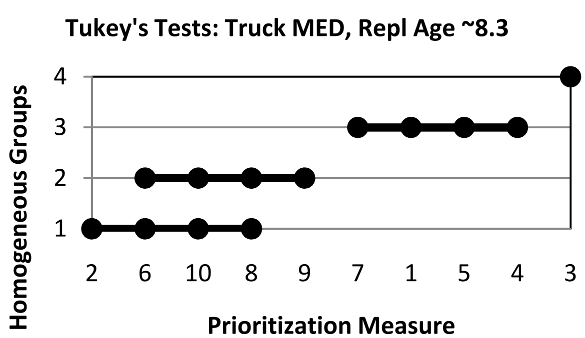
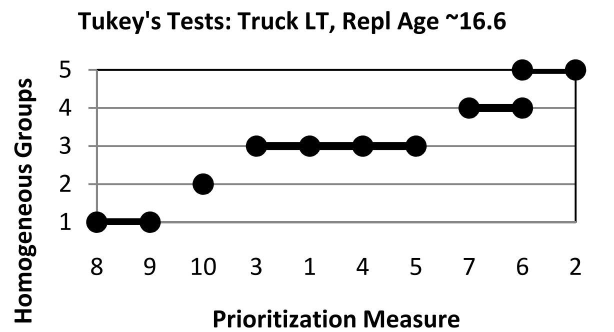
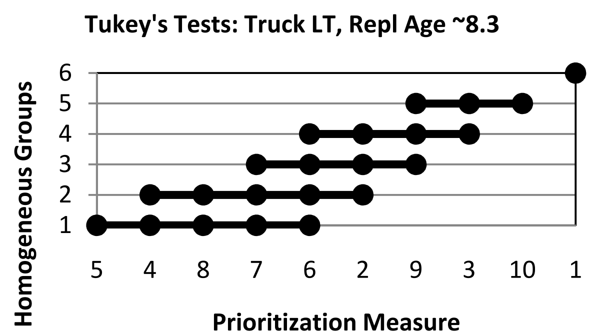
  	$MS_E = 0.0000152779$ $T_{\alpha=0.05} = 0.005698135$
  	$MS_E = 0.0000828115$ $T_{\alpha=0.05} = 0.013266191$

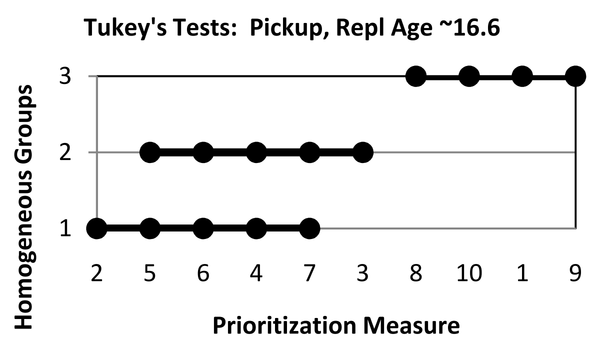
Table 23, Truck LT & Pickup: Tukey’s test for total cost per mile by prioritization measure

<table>
<tr>
<td>


</td>
<td rowspan="2">

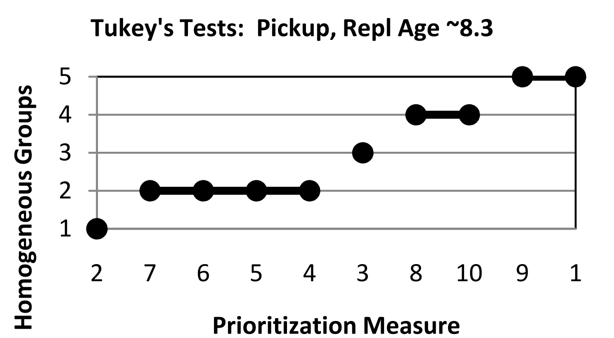
$MS_E = 0.00000741489$

$T_{\alpha=0.05} = 0.00396966$
</td>
</tr>
<tr>
<td>


</td>
</tr>
<tr>
<td>


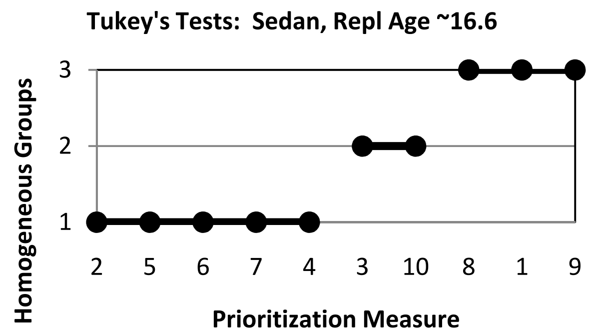
</td>
<td rowspan="2">

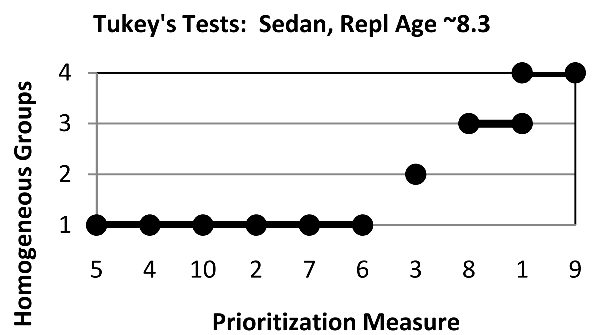
$MS_E = 0.00000199345$

$T_{\alpha=0.05} = 0.002058276$
</td>
</tr>
<tr>
<td>


</td>
</tr>
</table>

Table 24, Sedan: Tukey's multiple comparison test for total cost per mile by prioritization measure





$$MS_E = 0.000000843273$$

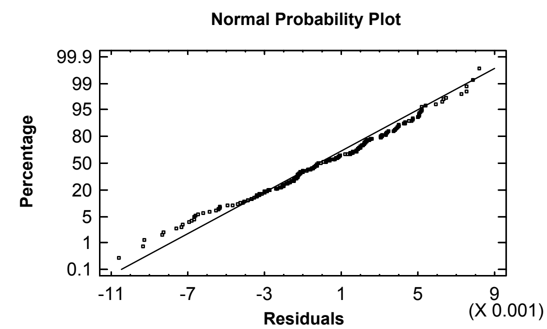
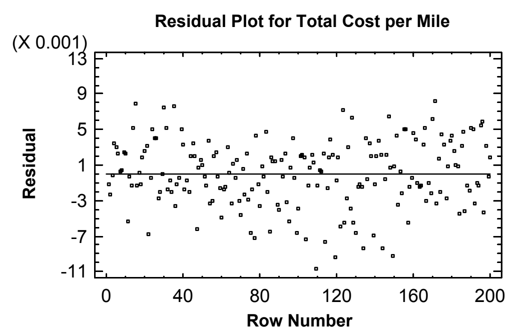
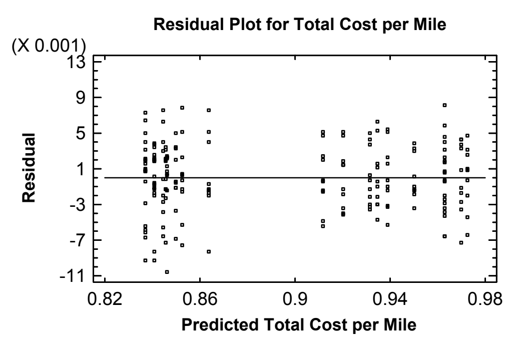
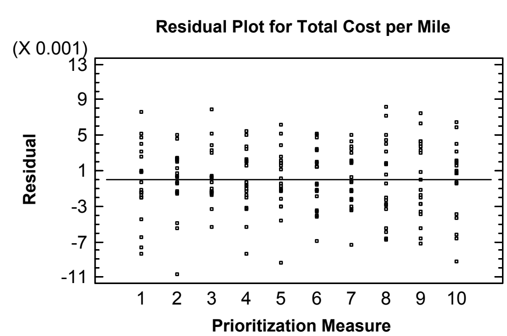
$$T_{\alpha=0.05} = 0.001338705$$

Results from Tukey's test are presented in graphs in Table 22, Table 23, and Table 24. For each analyzed set there is one graph. In each graph prioritization measures are sorted from lowest mean (left) to highest mean (right) which is represented by the x-axis labels. The y-axis in each graph is labeled with the number of homogeneous groups. Prioritization measures connected with a bold line form a group of means within which there are no statistically significant differences at a confidence level of 95 percent. Prioritization measures connected by the lowest bold line form the first homogeneous group. Thus, in this research the first homogeneous group of prioritization measures denotes a group of prioritization measures which causes the lowest and statistically indifferent means of total cost per mile for a certain average replacement age and a given equipment class.

4.2.4 Model adequacy checking

Analyses of variance as well as multiple comparison tests were performed for total cost per mile. Although parts of the same data (as in section 4.1) were utilized, this time the data was organized in a 2^1 x 10 full factorial design. Therefore, the underlying assumptions need to be verified.

Table 25, Truck HVY: Model adequacy checking for total cost per mile (2^1 x 10 factorial design)

<table>
<tr><td>
</td><td>The general impression from examining this normal probability plot of residuals is that the error distribution is approximately normal.</td></tr>
<tr><td>
</td><td>The plot of residuals versus row number provides no reason to suspect violation of the independence or constant variance assumptions.</td></tr>
<tr><td>
</td><td>The plot of residuals versus predicted total cost per mile provides no reason to suspect violation of the independence or constant variance assumptions.</td></tr>
<tr><td>
</td><td>The plot of residuals versus prioritization measure does not provide any reason to suspect violation of the independence or constant variance assumptions.</td></tr>
</table>

For both the ANOVA and Tukey's test, the errors of total cost per mile should be normally and independently distributed with mean zero and constant variance. This is verified for equipment class

Truck HVY (see Table 25). Residual analyses conducted for the other four equipment classes yield similar results. Model adequacy can be confirmed for each of the analyzed equipment classes. Thus, results from the ANOVA and Tukey's test in sections 4.2.1 and 4.2.3 are valid.

4.3 IMPLICATION ON FLEET COSTS

In section 4.2.3 the simulation results for total cost per mile dependent on prioritization measure and average replacement age were analyzed using Tukey's multiple comparison test. The term "first homogeneous group of prioritization measures" was defined, which denotes a group of replacement prioritization measures which produces lowest and statistically indifferent means of total cost per mile for a given average replacement age and a given equipment class. Next the results are analyzed to determine which prioritization measure belongs most often to the group of high performers, i.e. the first homogeneous group.

Total cost per mile plots for different equipment classes (see Table 19) indicated that different prioritization measures produce the lowest total cost per mile for different levels of average replacement age and different equipment classes. For each equipment class and each level of average replacement age a multiple comparison test was conducted in section 4.2.3. For each multiple comparison test, results are presented in a graph in Table 22, Table 23, and Table 24. In each graph the x-axis is labeled with prioritization measure numbers sorted from lowest (left) to highest (right) total cost per mile mean. In other words, prioritization measures are ranked based on their performance in the simulation which is evaluated by comparison of mean total cost per mile. Thus, for each equipment class and each level of average replacement age a ranking of prioritization measures can be established which is presented in Table 26 and Table 27. Table 26 shows rankings of prioritization measures and the corresponding means of total cost per mile for each of the analyzed equipment classes for average replacement age 8.3 years. Table 27 shows the same results for average replacement age 16.6 years. Moreover, in each ranking the first homogeneous group of replacement prioritization measures is shaded grey.

The count of how often individual prioritization measures appear in the first homogeneous groups (grey shaded areas in Table 26 and Table 27) is divided by the maximum number of possible appearances in the first homogeneous group. The percentage of appearance in the first homogeneous group is computed for average replacement age 8.3 years and 16.6 years separately, and for both levels combined. For average replacement age 8.3 years and 16.6 years the maximum number of possible appearances is five and for both levels combined the maximum number of possible appearances is hence ten. Results are plotted in Figure 6.

Since prioritization measures within a first homogeneous group produce statistically identical results for total cost per mile at a confidence level of 95 percent, there is no preference for a particular prioritization measure in this group. Analysis of relative appearance in Figure 6 reveals that measure two (replace oldest first) appears most often in the results for average replacement age 16.6 years and 16.6 and 8.3 years combined. Considering average replacement age 8.3 years only, measure two appears as often as measure four through six, eight and ten.

Table 26, Replacement prioritization measures ranked based on mean total cost per mile for average replacement age 8.3 years

Ranking	Sedan		Pickup		Truck LT		Truck MED		Truck HVY	
	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean
1	5	0.159024	2	0.280649	5	0.447442	2	0.930611	8	0.836895
2	4	0.15929	7	0.282965	4	0.447845	6	0.938446	10	0.836993
3	10	0.159488	6	0.28307	8	0.449301	10	0.940776	4	0.84066
4	2	0.159766	5	0.283707	7	0.450003	8	0.942633	5	0.840811
5	7	0.160158	4	0.284296	6	0.451343	9	0.945263	9	0.844684
6	6	0.16029	3	0.28816	2	0.451775	7	0.962612	7	0.84577
7	3	0.162047	8	0.294582	9	0.453836	1	0.968393	2	0.846201
8	8	0.164933	10	0.295352	3	0.454942	5	0.969443	6	0.849888
9	1	0.165134	9	0.298158	10	0.457524	4	0.970302	3	0.852362
10	9	0.166272	1	0.30015	1	0.468842	3	0.983592	1	0.86398

Table 27, Replacement prioritization measures ranked based on mean total cost per mile for average replacement age 16.6 years

Ranking	Sedan		Pickup		Truck LT		Truck MED		Truck HVY	
	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean	Priorit. Measure	Mean
1	2	0.186015	2	0.338837	8	0.517714	10	0.968155	2	0.91147
2	5	0.186124	5	0.339869	9	0.519548	8	0.980852	6	0.920462
3	6	0.186358	6	0.339969	10	0.525752	9	0.981539	7	0.93162
4	7	0.186486	4	0.340048	3	0.530269	1	0.984195	5	0.934821
5	4	0.186516	7	0.340055	1	0.531522	4	1.00744	4	0.938896
6	3	0.188267	3	0.340968	4	0.532199	3	1.01109	3	0.950193
7	10	0.189496	8	0.346263	5	0.533952	5	1.01134	8	0.963016
8	8	0.191887	10	0.347184	7	0.539078	7	1.01535	10	0.963057
9	1	0.191941	1	0.347414	6	0.542597	2	1.01957	9	0.970022
10	9	0.192192	9	0.348107	2	0.543707	6	1.01959	1	0.972363

Figure 6 indicates that prioritization measure two (replace oldest first) might be the most effective overall measure to prioritize replacement candidates in ODOT's fleet. In order to verify this assumption a sample fleet was set up according to data provided by ODOT. The sample fleet includes all five equipment classes analyzed in this research. Average values for annual mileage traveled per unit of equipment for each equipment class based on historical fleet data were calculated. The average replacement age for each equipment class was set to either 8.3 years or 16.6 years depending on which value was closer to the ODOT age standard for the class. The size of each equipment class is the same as in the actual ODOT fleet (see Table 3). For this sample fleet (see Table 28) annual operational fleet costs were estimated.

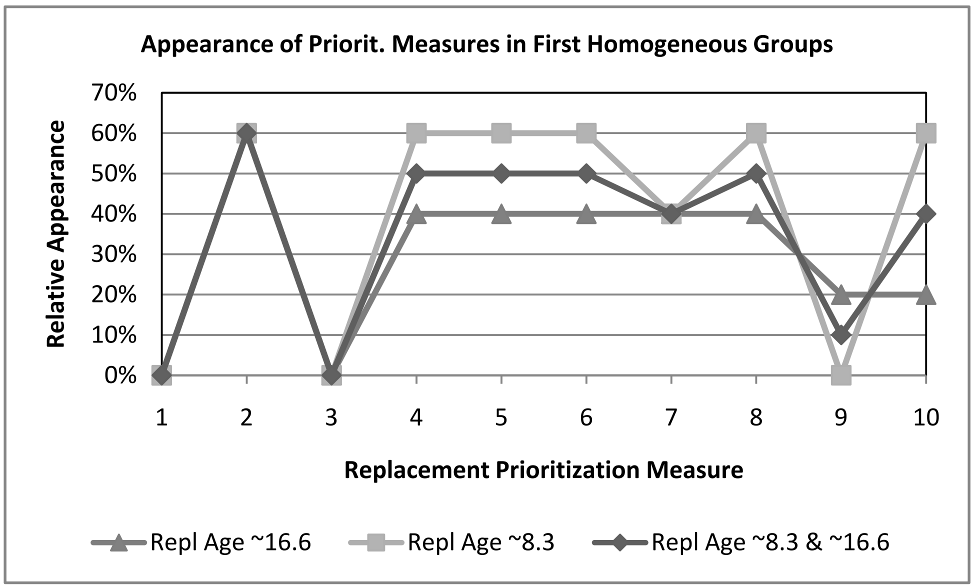


Figure 6, Relative appearance of replacement prioritization measures in first homogeneous groups

Table 28, ODOT sample fleet characteristics

Equipment Class	**Average Annual Mileage per Equipment Unit**	**Average Replacement Age**	**Number of Units**
Sedan	9,576	8.3	180
Pickup 3/4T 4X2	19,126	8.3	270
Truck LT 4X2	12,616	8.3	270
Truck MED 4X2 DSL	6,178	16.6	170
Truck HVY DSL	15,695	16.6	370

Operational costs are defined in Equation 4. Operational costs cover all costs produced by a piece of equipment in service except acquisition costs. Thus, operational costs are identical to total costs which were introduced in section 3.2.3.

Equation 4

$$\text{operational cost} = \text{repair cost} + \text{fix cost} + \text{operating cost}$$

The ODOT sample fleet characterized in Table 28 is composed of the five largest equipment classes managed by ODOT Fleet Services. The 1260 units of equipment considered in this sample fleet correspond to 25 percent of the roughly 5000 units in the ODOT fleet. In order to compute annual operational fleet costs produced by the sample fleet, the average annual mileage per equipment unit, number of units, and total cost per mile for each equipment class are multiplied and then summed. This computation is performed for every prioritization measure tested in this research. Corresponding values for total cost per mile are taken from Table 26 and Table 27. Note that depending on the average replacement age – which is assigned to equipment classes in Table 28 –either Table 26 or Table 27 is used as the source for total cost per mile. Results for annual operational costs produced by the sample fleet are plotted in Figure 7.

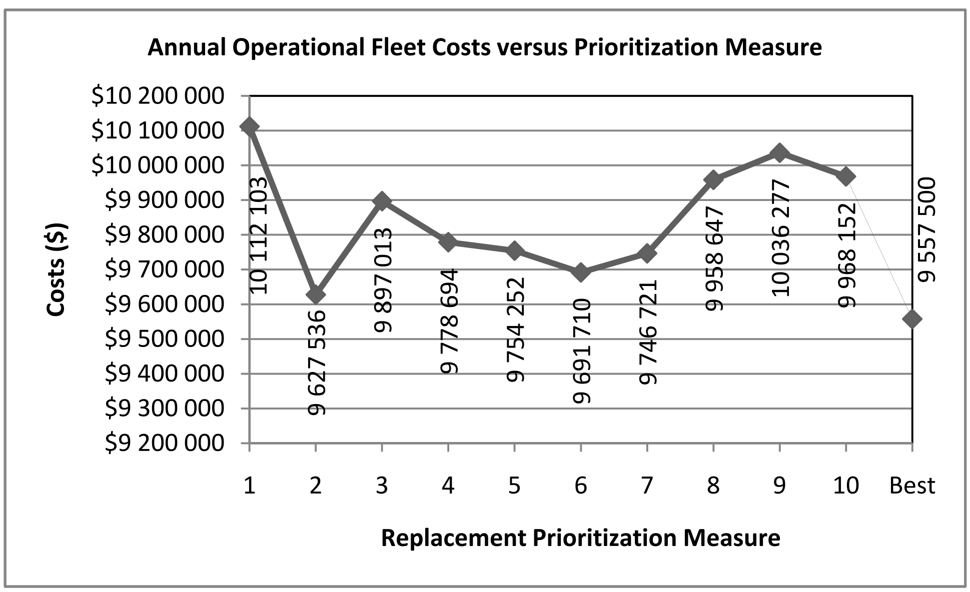


Figure 7, Annual operational costs produced by ODOT sample fleet versus replacement prioritization measure

Figure 7 shows annual operational costs produced by the ODOT sample fleet versus prioritization measure given that replacement decisions are made based on a single prioritization measure for the whole fleet. Prioritization measure two (replace oldest first) will produce the lowest annual operational costs. Measure six (modified ODOT model) will producethe second lowest operational costs and Measure one (replace randomly) will result in highest expenses for one year of fleet operation.

Prioritization measure two (replace oldest first) applied on the ODOT sample fleet will save annually 119,185 dollars compared to the the current ODOT model (measure seven) which equals 1.22 percent of annual operation expenses. If the highest ranked prioritization measure (see Table 26 and Table 27) for each class was used to make replacement decisions for each class, an additional 70,036 dollar could be saved, which is 1.94 percent of annual expenses. In Figure 7 and Figure 8 this scenario is labeled on the x-axes with “Best”. Further results for the potential savings due to the implementation of prioritization measure two compared to a selection of other prioritization measures are presented in Figure 8.

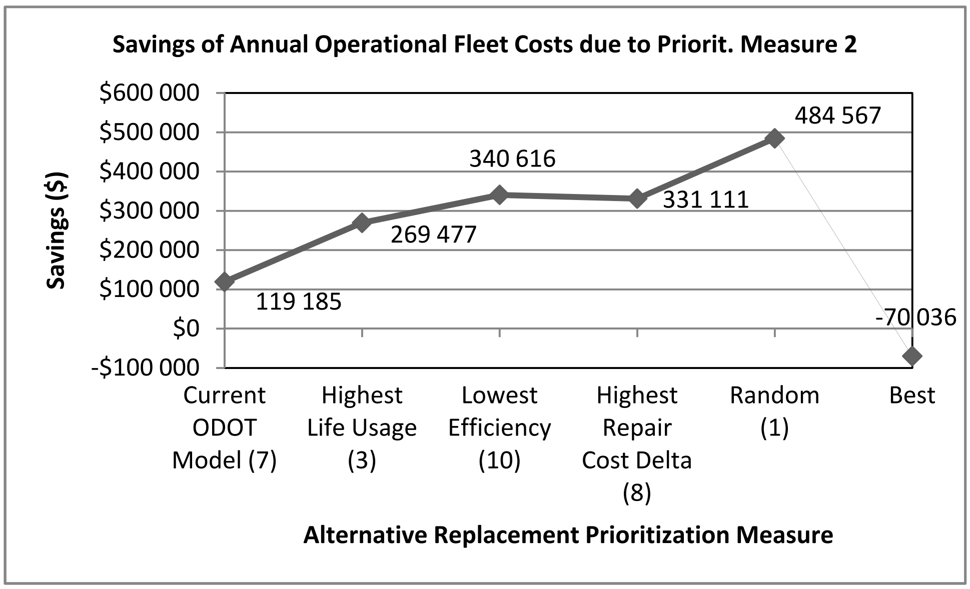


Figure 8, Savings of annual operational costs due to replacement prioritization measure two compared to selected alternative prioritization measures

5 DISCUSSION

We discuss three issues which we have recognized as relevant during this research. While using age and use standards in replacement prioritization measures we have realized that this area offers more research opportunities. Moreover, we discuss limitations concerning utilization and equipment acquisition which are inherent to the simulation approach presented in this research.

5.1 STANDARDS

In section 3.2.3 we have introduced ten replacement prioritization measures which were simulated and tested in this research. Two measures tested were the current ODOT model (measure seven) and the modified ODOT model (measure six). Both measures use age and use standards for normalization (see Table 14). We recognize that normalization serves two purposes:

1. Weighing components so that components are comparable and a reasonable replacement priority ranking emerges for a specific equipment class.

2. Weighing components so that created measures are comparable across equipment classes and a fleet wide replacement priority ranking emerges.

The capability to create a fleet wide replacement priority ranking by customizing standards to equipment classes or families of equipment classes is a very appealing idea because it corresponds to what transportation agencies expect from a replacement prioritization measure. The validity of such a prioritization measure relies heavily on the correctness of the implemented standards. In this research standards are given by ODOT Fleet Services. Further research is necessary to investigate if ranking performance can be improved by adjusting these standards and if measures should be extended with additional ratios using new types of standards.

5.2 UTILIZATION

Fleets of equipment exist to meet service demands generated by the organization utilizing the fleet. Economical and efficient fleet management meets these demands at the lowest possible cost. In this research, the service demand (total annual mileage) is not modeled explicitly. Instead, the total annual mileage is a model output. As a result, average annual mileage per equipment unit varies with the replacement prioritization measure tested (see Table 20, Table 21 and Table 44 through Table 46). This was done so that the costs and usage over time for vehicles in the simulation reflected the cost and usage patterns found in ODOT historical data. Therefore, a transfer of the results generated in this research to an environment with a fixed usage demand must be made. We have assumed that using a cost per mile measure accomplishes this.

5.3 ACQUISITION

In section 3.2.5 we have introduced four factors whose effects on total cost per mile were then scrutinized. In section 4.1.1 we have shown that correlation, replacement age, and replacement prioritization measure do have a statistically significant effect on total cost per mile while fleet size does not. Correlation is not an option but a given fact found in historical ODOT data. Replacement age is a parameter that can be adjusted by fleet management. In this research we considered two levels of average replacement age. An average replacement age 8.3 years implies that on average 24 percent of the fleet is replaced every other year. An average replacement age 16.6 years implies a turnover rate of 12 percent every other year. The decision for one or the other replacement age has substantial effect on acquisition costs, resale value, and total cost per mile (see Table 19). We cannot predict which factor outweighs the other and which policy is in total the most cost effective.

This research does not address the question of replacement budget, replacement intervals, and what the average replacement age for an equipment class should be. This research does focuses on how operational fleet costs – including repair costs, fix costs, and operating costs – can be minimized by choosing the optimal replacement prioritization measure given that every other year a fixed number of replacements are made.

Nevertheless, many fleet managers do not have sufficient funds to introduce a cost optimal acquisition schedule which may require a large number of acquisitions to start. Rather, many transportation agencies face tight budgets and want to know how to use this fixed budget in the most reasonable way. In this research we adopt these circumstances.

6 CONCLUSION

Multifactor analyses of variance and interaction plots in sections 4.1.1, 4.2.1, and 4.2.2 show that the factors replacement prioritization measure, correlation in the data, and average replacement age do have a statistically significant and economically substantial effect on total cost per mile. Factor fleet size emerged as statistically insignificant and economically irrelevant for total cost per mile. The factor correlation shows a significant and relevant interaction with the factor prioritization measure (see Figure 2). Hence, some prioritization measures are promoted and others are deteriorated in their performance depending on the inclusion of correlation.

The results suggest that replacement prioritization measures one (replace randomly) and three (replace highest life usage first) should not be used. These measures are not in any homogeneous group of best performers (see Figure 6) for any vehicle class tested. While the poor performance of “replace randomly” supports the validity of using a model, the results for measure three require explanation. A closer look at selected interaction plots from all five equipment classes (see Table 20, Table 21 and Table 44 through Table 46) reveals that measure three persistently promotes low utilization levels while costs are not under control. In other words, “replace highest life usage first” eliminates highly utilized units of equipment from the fleet which does have a negative effect on the average total cost per mile.

There is evidence that measure six (modified ODOT model) is superior to measure seven (ODOT model), i.e. that life usage divided by acquisition costs deteriorates ranking performance. Figure 6 shows that measure seven is less prevalent among high performing measures at average replacement age 8.3 years than measure six. Figure 7 shows that annual operational costs produced by the ODOT sample fleet are lower with measure six than with measure seven. The stronger the influence of parameter equipment age on the ranking outcome, the better the corresponding ranking performs. However, for average replacement age 16.6 years, the results show equal performance between measure seven and measure six.

The performance of measure ten (replace lowest efficiency first) ranks in the middle. Similar to measure eight (replace highest repair cost delta first) and nine (replace highest total cost delta first) measure ten promotes high levels of average replacement age and low levels of annual mileage (see Table 20, Table 21 and Table 44 through Table 46). Still, measure ten does not succeed in persistently maintaining an extraordinary efficient fleet, i.e. a fleet showing extraordinary low total cost per mile (see Table 26 and Table 27).

Replacement prioritization measure two (replace oldest first), six (modified ODOT model), and seven (ODOT model) promote high levels of annual mileage per equipment unit and a low average equipment age. Measures eight (replace highest repair cost delta first) and nine (replace highest total cost delta first) promote low levels of annual mileage per equipment unit and a high average equipment age. This result appears persistently in all five equipment classes (see Table 20, Table 21 and Table 44 through Table 46). A closer look at these tables reveals that there exist two types of equipment. For Truck HVY (at average replacement age 16.6 years), Pickup, and Sedan (at average replacement age 8.3 years) the total cost per mile are at the lowest point when utilization is high and average equipment age is low. For Truck MED and Truck LT (at average replacement age 16.6 years) total cost per mile are at the lowest point when utilization is low and the average equipment age is high. Hence, measures two, six, and seven perform well with Truck HVY, Pickup and Sedan while measures eight and nine perform well with Truck MED and Truck LT. This result is confirmed by multiple comparison tests (see Table 26 and Table 27).

Multiple comparison tests for total cost per mile show that there is not a single replacement prioritization measure which dominates statistically significantly across all five equipment classes (see Figure 6). However, given that a single prioritization measure has to be chosen for application on an actual fleet similar to ODOT's fleet, measure two (replace oldest first) results in lowest operational fleet costs per year. "Replace oldest first" applied on the ODOT sample fleet which is described in more detail in section 4.3 saves $ 119,000 in annual operational costs compared to the "ODOT model" which is currently used by ODOT Fleet Services. This corresponds to 1.22 percent of total operational costs per year for this fleet. Moreover, "replace oldest first" results in higher or equal annual mileage per equipment unit and a lower or equal average equipment age compared to the "ODOT model".

BIBLIOGRAPHY

Ayres, R.M. and Waizeneker, J. (1978): A practical approach to vehicle replacement; *Chartered Mechanical Engineer*, vol. 25, no. 9, pp. 73-75.

Buddhakulsomsiri, J., Parthanadee, P. (2006): Parallel replacement problem for a fleet with dependent use; *Industrial Engineering Research Conference (IERC)*, Orlando, FL.

Chee, P.C.F. (1975): A practical vehicle replacement policy for Ontario Hydro; *Ontario Hydro Research Quarterly,* vol. 27, no. 3, Third Quarter, pp. 3-6.

Oracle Crystal Ball (2008): Reference Manual; Fusion Edition, Release 11.1.1.1.00, Oracle.

Davenport, N.S., Anderson, M.D. and Farrington, P.A. (2005): Development and application of a vehicle procurement model for rural fleet asset management; *Transportation Research Record*, no. 1927, pp. 123-127.

Dhillon, B.S. (1989): Life Cycle Costing; *Gordon and Breach Science Publishers*, New York.

Drinkwater, R.W. and Hastings, N.A.J. (1967): An economic replacement model; *Operational Research Society*, OR, vol. 18, no. 2 (Jun., 1967), pp. 121-138.

Eilon, S., King, J. R. and Hutchinson D. E. (1966): A Study in Equipment Replacement; *Operational Research Society*, OR, vol. 17, no. 1, pp. 59-71.

Grant, E.L., Ireson, W.G. and Leavenworth, R.S. (1990): Principles of Engineering Economy; *John Wiley and Sons*, New York.

Hartman, J. C. (1999): A general procedure for incorporating asset utilization decisions into replacement analysis; *Engineering Economist*, vol. 44, no. 3, pp. 217.

Hartman, J. C. (2004): Multiple asset replacement analysis under variable utilization and stochastic demand; *European Journal of Operational Research*, vol. 159, no. 1, pp. 145-165.

Hastings, N.A.J. (1969): The Repair Limit Replacement Method; *Operational Research Society,* OR, vol. 20, no. 3, pp. 337-349.

Khasnabis, S., Bartus, J. and Ellis, R.D. (2003): Asset management framework for state departments of transportation to meet transit fleet requirements; *Transportation Research Record*, no. 1835, pp. 74-83.

Little, J.D.C. (1961): A Proof for the Queuing Formula: $L = \lambda W$; *Operations Research*, vol. 9, no. 3, pp. 383-387.

Love, C.E., Rodger, R. and Blazenko, G. (1982): Repair limit policies for vehicle replacement; *INFOR Journal,* vol. 20, pp. 226-37.

Montgomery, D.C. (2005): Design of Experiments; 6th Edition, John Wiley & Sons

Nakagawa, T. and Osaki, S. (1974): The Optimum Repair Limit Replacement Policies; *Operational Research Quarterly*, vol. 25, no. 2, pp. 311-317.

Odeck, J. and Hjalmarsson, L. (1996): The performance of trucks - An evaluation using data envelopment analysis; *Transportation Planning and Technology*, vol. 20, no. 1, pp. 49-66.

Redmer, A. (2005): Vehicle replacement planning in freight transportation companies; *Proceedings of the 16th Mini - EURO Conference and 10th Meeting of EURO Working Group Transportation*, Poznan, Poland.

Rees, L.P., Clayton, E.R. and Taylor, B.W.III (1982): Network simulation model for police patrol vehicle maintenance and replacement analysis; *Computers, Environment and Urban Systems*, vol. 7, no. 3, pp. 191-196.

Simms, B.W., Lamarre, B.G. and Jardine, A.K.K. (1984): Optimal buy, operate and sell policies for fleets of vehicles; *European Journal of Operational Research*, vol. 15, no. 2, pp. 183-195.

Tukey, J.W. (1953): The Problem of Multiple Comparisons; Unpublished Notes, Princeton University.

Venkatakrishnan, K.S. and Venmathi, S. (1989): Optimal replacement time of equipment via simulation for truncated failure distributions; *Microelectronics and Reliability*, vol. 29, no. 1, pp. 49-52.

Weissmann, J., Weissmann, A.J. and Gona, S. (2003): Computerized equipment replacement methodology; *Transportation Research Record*, no. 1824, pp. 77-83.

APPENDIX

Table 29, Literature review: Equipment replacement models particularly used for vehicle fleets

Paper Details				Replacement Criteria					Utilization		
Source	**Purpose**	**Fleet**	**Model**	**Mileage/Hours**	**Age**	**Operating cost**	**Repair cost**	**Repair time**	**Implementation as**	**Consideration**	**Classification**
Davenport, N.S., Anderson, M.D. and Farrington, P.A. (2005): Development and application of a vehicle procurement model for rural fleet asset management	Fleet condition forecast	Cutaway passenger vans	Regression model						Parameter	Considered	Non cost minimization
Khasnabis, S., Bartus, J. and Ellis, R.D. (2003): Asset management framework for state departments of transportation to meet transit fleet requirements	Find optimal capital allocation for the dual purpose of purchasing new assets and rebuilding existing ones within the constraint of a fixed budget	Medium sized buses	Linear optimization							Not considered	
Rees, L.P., Clayton, E.R. and Taylor, B.W.III (1982): Network simulation model for police patrol vehicle maintenance and replacement analysis	Replacement demand forecast	Police patrol fleet	Markov type simulation							Implicitly constant	
Love, C.E., Rodger, R. and Blazenko, G. (1982): Repair limit policies for vehicle replacement	Find the optimal life time limit and find the optimal repair cost limit. Compare both replacement criteria.	Postal Canada fleet	LCCA: Nonlinear programming; Repair cost limit: Markov decision process		x		x			Implicitly constant	Comparison
Venkatakrishnan, K.S. and Venmathi, S. (1989): Optimal replacement time of equipment via simulation for truncated failure distributions	Comparison of life time limit derivation: LCCA vs. Monte Carlo Simulation	Asset independent	LCCA: Nonlinear programming; Repair cost limit: Monte Carlo simulation		x					Not considered	

Table 30, Literature review: Equipment replacement models particularly used for vehicle fleets (Continued)

Ayres, R.M. and Waizeneker, J. (1978): A practical approach to vehicle replacement	Find the optimal life time limit	Transportation fleet	Nonlinear programming		x					Implicitly constant	**Life time limit (LCCA)**
Chee, P.C.F. (1975): A practical vehicle replacement policy for Ontario Hydro	Find the optimal life time limit and repair cost limit	Ontario Hydro fleet	Non-mathematical model		x		x			Constant	
Eilon, S., King, J.R. and Hutchinson D.E. (1966): A Study in Equipment Replacement	Find the optimal life time limit	Fork lift trucks	Nonlinear programming		x					Implicitly constant	
Redmer, A. (2005): Vehicle replacement planning in freight transportation companies	Find the optimal life time limit	Freight transportation fleet	Linear programming		x				Parameter	Decreasing as assets grow older / Constant for assets with the same age	
Weissmann, J., Weissmann, A.J. and Gona, S. (2003): Computerized equipment replacement methodology	Find the optimal life time limit and identify a valid multi attribute asset ranking	Texas DOT fleet	Nonlinear programming	x	x	x	x			Implicitly constant	
Drinkwater, R.W. and Hastings, N.A.J. (1967): An economic replacement model	Find the optimal repair cost limit	Non armored army fleet	Dynamic programming and Monte Carlo simul.				x			Not considered	**Repair cost limit**
Hastings, N.A.J. (1969): The Repair Limit Replacement Method	Find the optimal repair cost limit	Single asset case	Dynamic programming				x			Not considered	
Nakagawa, T. and Osaki, S. (1974): The Optimum Repair Limit Replacement Policies	Find the optimal repair time limit	Single asset case	Nonlinear programming					x		Not considered	
Buddhakulsomsiri, J., Parthanadee, P. (2006): Parallel replacement problem for a fleet with dependent use	Find the optimal replacement schedule	Not specified real fleet	Linear programming						Parameter	Decreasing as assets grow older / Constant for assets with the same age	**Comprehensive cost minimization**
Hartman, J.C. (1999): A general procedure for incorporating asset utilization decisions into replacement analysis	Find the optimal replacement schedule and associated utilizations	Multi asset case	Linear programming						Decision variable	Function of deterministic demand	
Hartman, J.C. (2004): Multiple asset replacement analysis under variable utilization and stochastic demand	Find the optimal replacement schedule and associated utilizations levels	Two asset case	Stochastic dynamic programming						Decision variable	Function of stochastic demand	
Simms, B.W., Lamarre, B.G. and Jardine, A.K.K. (1984): Optimal buy, operate and sell policies for fleets of vehicles	Find the optimal replacement schedule and associated utilizations levels	Urban transit bus fleet	Dynamic and linear programming						Decision variable	High for young assets / Low for old assets	

Table 31, Number of mileage records over equipment age for selected equipment classes (columns with less than 20 records per year have been cleared)

	M_01	M_02	M_03	M_04	M_05	M_06	M_07	M_08	M_09	M_10	M_11	M_12	M_13	M_14	M_15	M_16	M_17	M_18	M_19	M_20	M_21	M_22	M_23	M_24	M_25
Sedan	108	95	79	88	83	63	42	42	23	23	23	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pickup	233	183	161	147	87	71	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Truck LT	200	149	164	101	105	73	73	43	33	33	25	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Truck MED	60	40	85	72	97	95	95	109	117	100	103	58	58	33	33	36	0	0	0	0	0	0	0	0	0
Truck HVY	167	185	215	194	226	144	160	133	144	144	93	87	87	55	55	40	36	25	26	27	0	0	0	0	0

Table 32, Deviation between original and generated sample means and standard deviations under consideration of correlation

Equipment Class	$\sigma(\Delta^{\%}_{Mean})$	$\sigma(\Delta^{\%}_{StdDev})$
Sedan	0.0177	0.0945
Pickup	0.0115	0.0441
Truck LT	0.0181	0.1247
Truck MED	0.0294	0.1674
Truck HVY	0.0227	0.1664

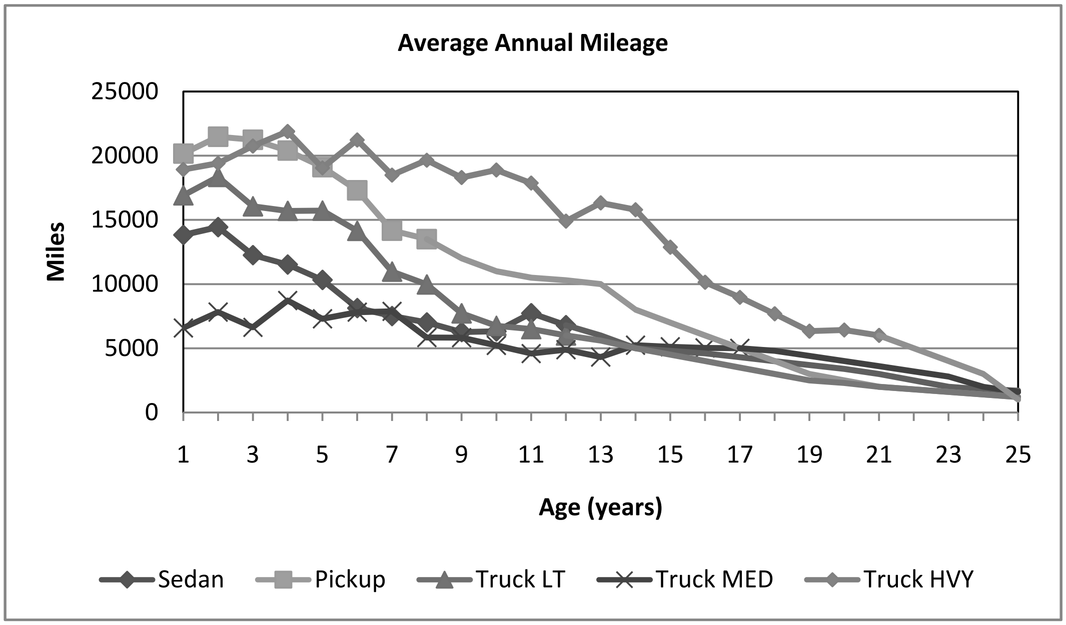


Figure 9, Means of annual mileage based on historical ODOT data and forecasted means (where markers end) versus equipment age

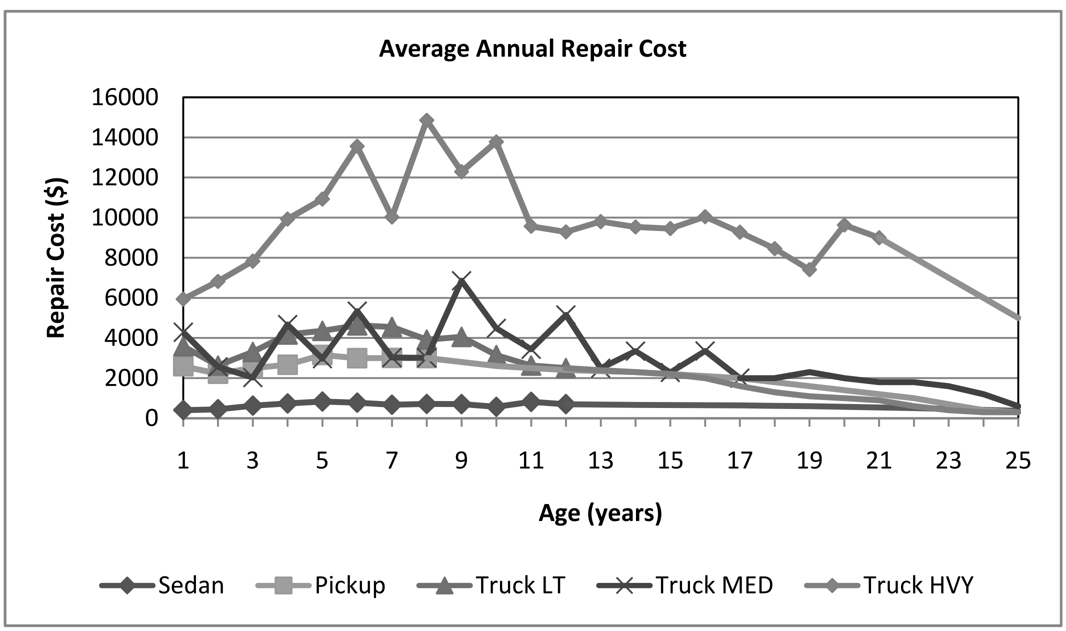


Figure 10, Means of annual repair cost based on historical ODOT data and forecasted means (where markers end) versus equipment age

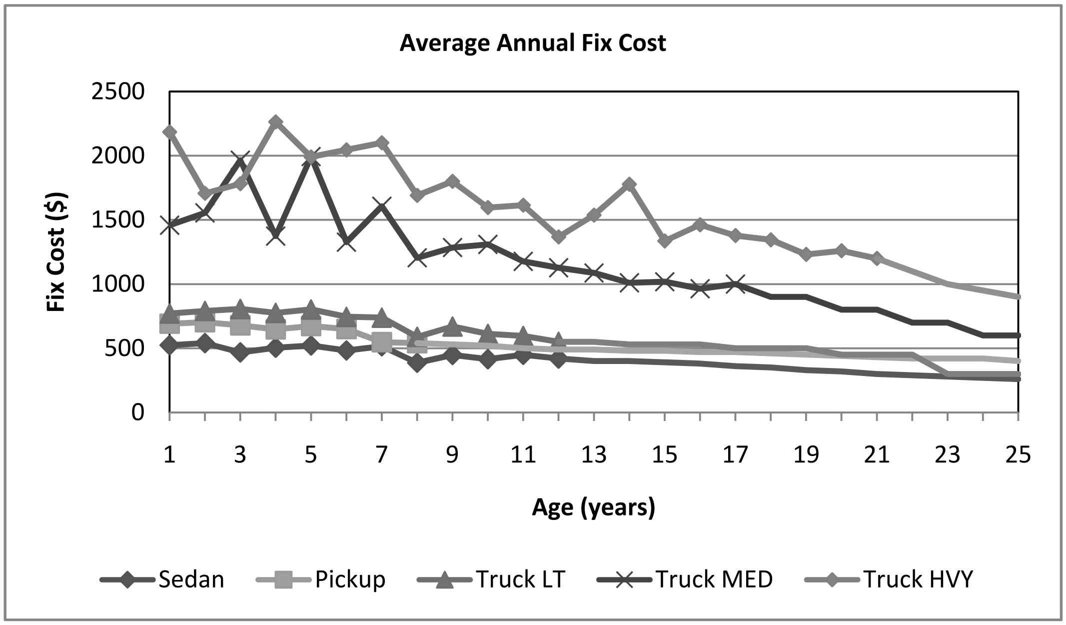


Figure 11, Means of annual fix cost based on historical ODOT data and forecasted means (where markers end) versus equipment age

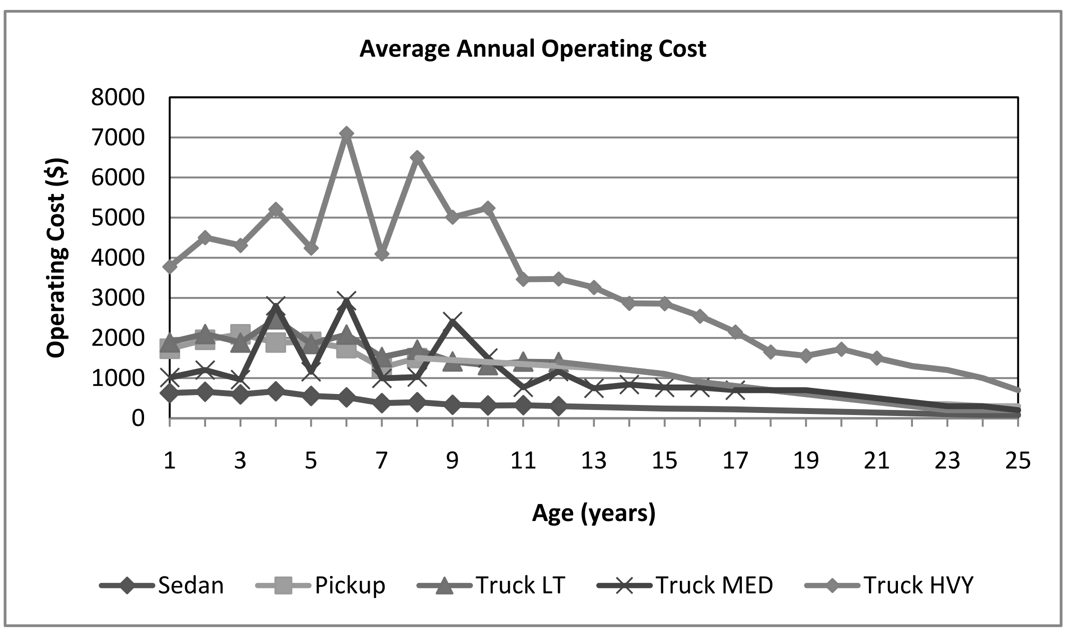


Figure 12, Means of annual operating cost based on historical ODOT data and forecasted means (where markers end) versus equipment age

Table 33, Price inflators used to normalize costs generated by ODOT equipment to the price level of ODOT accounting year 2001/2002

Accounting Year	Price Inflator for Repair Cost	Price Inflator for Fix Cost	Price Inflator for Operating Cost	Price Inflator for Acquisition Cost
2001/2002	1	1	1	1
2000/2001	1.0367	1.0699	0.8546	0.9898
1999/2000	1.0725	1.0943	0.9659	0.9880
1998/1999	1.1024	1.1002	1.2404	0.9852
1997/1998	1.1351	1.0980	1.1373	0.9817
1996/1997	1.1633	1.1239	1.0607	0.9765
1995/1996	1.1982	1.1668	1.1102	0.9917
1994/1995	1.2294	1.2172	1.1193	1.0104
1993/1994	1.2634	1.2611	1.1821	1.0441
1992/1993	1.3026	1.3223	1.1335	1.0789
1991/1992	1.3452	1.3995	1.1630	1.1056
1990/1991	1.4071	1.5163	1.0780	1.1416
1989/1990	1.4676	1.6215	1.2549	1.1729
1988/1989	1.5294	1.7225	1.3370	1.1934
1987/1988	1.5958	1.8487	1.3951	1.2219
1986/1987	1.6620	1.9741	1.5359	1.2495
1985/1986	1.7229	2.1978	1.2361	1.3073
1984/1985	1.7761	2.4703	1.1668	1.3520
1983/1984	1.8328	2.6733	1.1375	1.3926
1982/1983	1.8995	2.9068	1.1296	1.4303
1981/1982	2.0168	3.1556	1.0791	1.4662
1980/1981	2.1873	3.3241	1.0966	1.5489
1979/1980	2.4119	3.5303	1.2945	1.6587
1978/1979	2.6623	3.8030	1.9849	1.7886
1977/1978	2.9098	3.9169	2.2561	1.9277
1976/1977	3.1337	4.1910	2.3398	2.0563
1975/1976	3.3584	5.0632	2.4400	2.1688

Table 34, Truck HVY: Analysis of variance for total cost per mile; 2^3 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0824148	9	0.0091572	517.40	0.00
B:Correlation	0.000104176	1	0.000104176	5.89	0.0158
C:Repl Age	0.908421	1	0.908421	51327.69	0.00
D:Fleet Size	0.00000138518	1	0.00000138518	0.08	0.7798
Interactions					
AB	0.0156668	9	0.00174075	98.36	0.00
AC	0.0419223	9	0.00465803	263.19	0.00
AD	0.000024578	9	0.00000273089	0.15	0.9978
BC	0.00198621	1	0.00198621	112.22	0.00
BD	0.000000367279	1	0.000000367279	0.02	0.8855
CD	0.000471156	1	0.000471156	26.62	0.00
ABC	0.00134365	9	0.000149295	8.44	0.00
ABD	0.0000367455	9	0.00000408284	0.23	0.9899
ACD	0.0000774167	9	0.00000860186	0.49	0.8838
BCD	0.00000985644	1	0.00000985644	0.56	0.4561
ABCD	0.0000507217	9	0.00000563575	0.32	0.9687
Residual	0.00566351	320	0.0000176985		
Total	1.05819	399			

Table 35, Truck HVY: Analysis of variance for total cost per mile; 2^1 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0250037	9	0.00277819	181.84	0.00
B:Repl Age	0.497681	1	0.497681	32575.23	0.00
Interaction					
AB	0.021947	9	0.00243856	159.61	0.00
Residual	0.00275002	180	0.0000152779		
Total	0.547381	199			

Table 36, Truck MED: Analysis of variance for total cost per mile; 2^3 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0343482	9	0.00381647	55.64	0.00
B:Correlation	0.00215979	1	0.00215979	31.49	0.00
C:Repl Age	0.200499	1	0.200499	2922.96	0.00
D:Fleet Size	0.000272125	1	0.000272125	3.97	0.0472
Interactions					
AB	0.00784987	9	0.000872208	12.72	0.00
AC	0.0492821	9	0.00547579	79.83	0.00
AD	0.000207167	9	0.0000230185	0.34	0.9627
BC	0.000000502103	1	0.000000502103	0.01	0.9319
BD	0.0000994174	1	0.0000994174	1.45	0.2295
CD	0.000003061	1	0.000003061	0.04	0.8328
ABC	0.0045643	9	0.000507144	7.39	0.00
ABD	0.000100163	9	0.0000111292	0.16	0.9973
ACD	0.0000608144	9	0.00000675716	0.10	0.9996
BCD	0.000117952	1	0.000117952	1.72	0.1907
ABCD	0.0000594986	9	0.00000661096	0.10	0.9997
Residual	0.0219502	320	0.0000685945		
Total	0.321574	399			

Table 37, Truck MED: Analysis of variance for total cost per mile; 2^1 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0361662	9	0.00401847	48.53	0.00
B:Repl Age	0.0999326	1	0.0999326	1206.75	0.00
Interaction					
AB	0.0248028	9	0.00275586	33.28	0.00
Residual	0.0149061	180	0.0000828115		
Total	0.175808	199			

Table 38, Truck LT: Analysis of variance for total cost per mile; 2^3 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.00504087	9	0.000560097	66.46	0.00
B:Correlation	0.000134885	1	0.000134885	16.00	0.0001
C:Repl Age	0.597694	1	0.597694	70917.28	0.00
D:Fleet Size	0.00000032347	1	0.00000032347	0.04	0.8448
Interactions					
AB	0.00155369	9	0.000172632	20.48	0.00
AC	0.0128117	9	0.00142352	168.90	0.00
AD	0.0000714141	9	0.0000079349	0.94	0.4891
BC	0.000107706	1	0.000107706	12.78	0.0004
BD	0.0000000843518	1	0.0000000843518	0.01	0.9204
CD	0.0000601495	1	0.0000601495	7.14	0.0079
ABC	0.000237367	9	0.0000263741	3.13	0.0013
ABD	0.00000979867	9	0.00000108874	0.13	0.9989
ACD	0.000052058	9	0.00000578422	0.69	0.7213
BCD	0.0000388346	1	0.0000388346	4.61	0.0326
ABCD	0.0000152434	9	0.00000169371	0.20	0.994
Residual	0.00269697	320	0.00000842804		
Total	0.620525	399			

Table 39, Truck LT: Analysis of variance for total cost per mile; 2^1 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.00470716	9	0.000523017	70.54	0.00
B:Repl Age	0.306924	1	0.306924	41392.95	0.00
Interaction					
AB	0.00592151	9	0.000657945	88.73	0.00
Residual	0.00133468	180	0.00000741489		
Total	0.318888	199			

Table 40, Pickup: Analysis of variance for total cost per mile; 2^3 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0165939	9	0.00184377	826.97	0.00
B:Correlation	0.0000501133	1	0.0000501133	22.48	0.00
C:Repl Age	0.283643	1	0.283643	127220.20	0.00
D:Fleet Size	0.00000856095	1	0.00000856095	3.84	0.0509
Interactions					
AB	0.00112239	9	0.00012471	55.94	0.00
AC	0.00151963	9	0.000168847	75.73	0.00
AD	0.0000173595	9	0.00000192884	0.87	0.5568
BC	0.0000254512	1	0.0000254512	11.42	0.0008
BD	0.000013545	1	0.000013545	6.08	0.0142
CD	0.000000792481	1	0.000000792481	0.36	0.5515
ABC	0.000123869	9	0.0000137633	6.17	0.00
ABD	0.00000637968	9	0.000000708854	0.32	0.9689
ACD	0.0000250542	9	0.00000278379	1.25	0.2646
BCD	0.0000954907	1	0.0000954907	42.83	0.00
ABCD	0.00000624379	9	0.000000693754	0.31	0.9711
Residual	0.000713453	320	0.00000222954		
Total	0.303965	399			

Table 41, Pickup: Analysis of variance for total cost per mile; 2^1 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.00545164	9	0.000605737	303.86	0.00
B:Repl Age	0.144521	1	0.144521	72498.00	0.00
Interaction					
AB	0.000579778	9	0.0000644198	32.32	0.00
Residual	0.00035882	180	0.00000199345		
Total	0.150911	199			

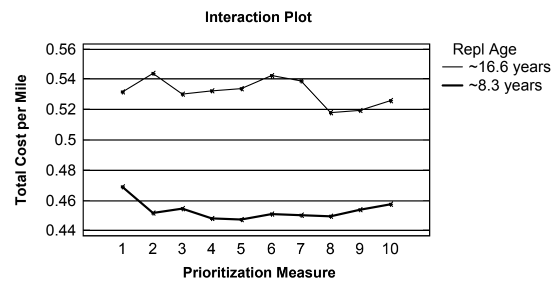
Table 42, Sedan: Analysis of variance for total cost per mile; 2^3 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

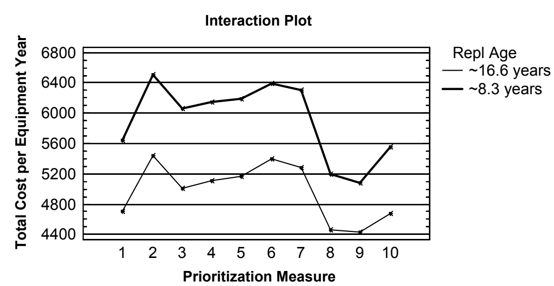
Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.0026648	9	0.000296089	366.38	0.00
B:Correlation	0.00000491301	1	0.00000491301	6.08	0.0142
C:Repl Age	0.0741091	1	0.0741091	91702.91	0.00
D:Fleet Size	0.000000890162	1	0.000000890162	1.10	0.2947
Interactions					
AB	0.0001962	9	0.0000218	26.98	0.00
AC	0.0000511379	9	0.00000568199	7.03	0.00
AD	0.00000359178	9	0.000000399087	0.49	0.8785
BC	0.0000112239	1	0.0000112239	13.89	0.0002
BD	0.000000618963	1	0.000000618963	0.77	0.3821
CD	0.00000685174	1	0.00000685174	8.48	0.0038
ABC	0.0000211947	9	0.00000235496	2.91	0.0025
ABD	0.000000888932	9	0.0000000987702	0.12	0.9991
ACD	0.00000343498	9	0.000000381664	0.47	0.8929
BCD	0.000000132581	1	0.000000132581	0.16	0.6857
ABCD	0.00000149797	9	0.000000166441	0.21	0.9934
Residual	0.000258606	320	0.000000808143		
Total	0.0773351	399			

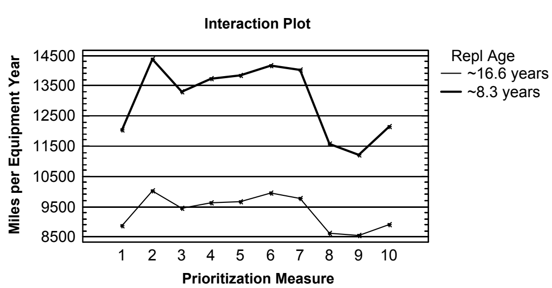
Table 43, Sedan: Analysis of variance for total cost per mile; 2^1 x 10 factorial design of experiment (All F-ratios are based on the residual mean square error)

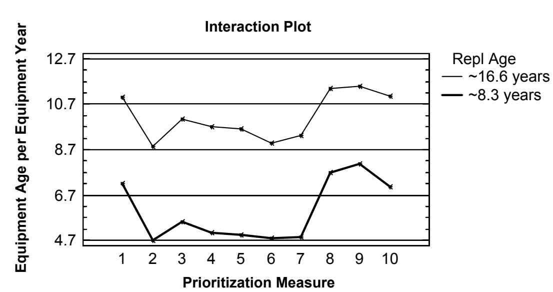
Source	Sum of Squares	Df	Mean Square	F-Ratio	P-Value
Main Effects					
A:Priorit Measure	0.00125234	9	0.000139149	165.01	0.00
B:Repl Age	0.0361481	1	0.0361481	42866.47	0.00
Interaction					
AB	0.0000634026	9	0.00000704473	8.35	0.00
Residual	0.000151789	180	0.000000843273		
Total	0.0376157	199			

Table 44, Truck LT: Comparison of selected interaction plots









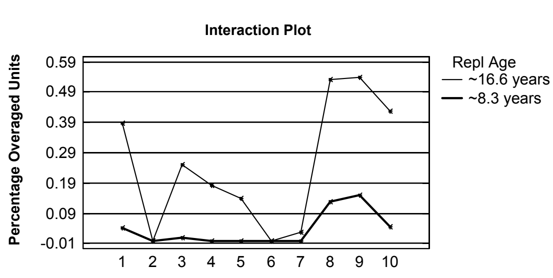
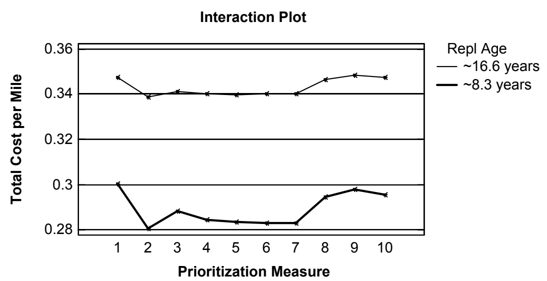
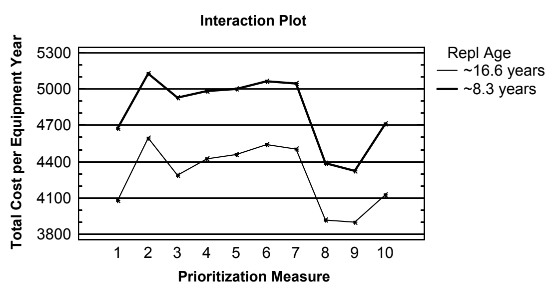
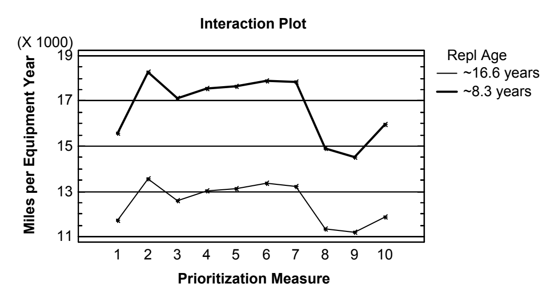
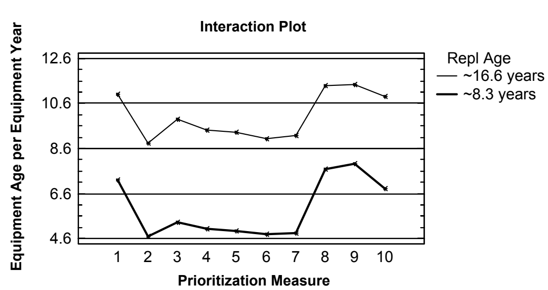


Table 45, Pickup: Comparison of selected interaction plots









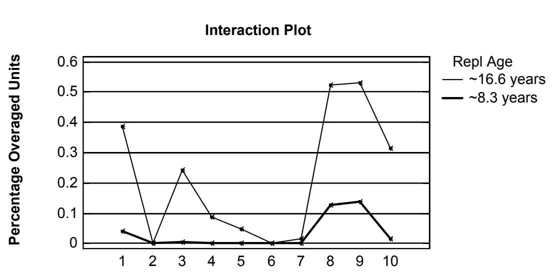


Table 46, Sedan: Comparison of selected interaction plots