GIS-based Integrated Rural and Small Urban Transit Asset Management System

Final Report—December 2003

MTC
MIDWEST TRANSPORTATION CONSORTIUM

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This study developed a methodology for improving the practice of making transit asset investment decisions at state departments of transportation and local transit agencies. The results of a literature review indicated that the majority of studies find there are significant differences in vehicle operating costs between road types (i.e., bituminous versus gravel versus earth), age, mileage, and vehicle type. Vehicle repair/maintenance cost is found to be primarily affected by vehicle condition. In terms of non-vehicle operating costs, vehicle downtime due to maintenance work and road calls due to vehicle breakdowns on the road were extensively studied in relation to vehicle condition.

The major capability of the new vehicle deterioration model developed under this study is to predict the future condition of the vehicle based on the historical records of the selected dependent factors, such as vehicle's age, mileage, and current conditions. The contribution of possible variables was analyzed, and the factors that affect the vehicle future conditions were specified. The model can identify the relative importance of the independent variables with the given condition ratings shown. In addition, predictions can be made for individual vehicles or a group of vehicles at different condition ratings, both of which are important for the management system. Knowing the percentages of vehicles at different condition ratings in the future, based on the present and historical conditions, a transit fleet manager can allocate the budget more efficiently and accurately.

This study also developed relationships between vehicle conditions and the cost of preventive and corrective maintenance and a life cycle cost analysis (LCCA) methodology incorporating these cost relationships into network-level and project-level decisions. One can use these relationships and LCCA to select the best maintenance strategies for short- and long-term operations. The models can help in making decisions regarding which applicable maintenance to use on the basis of minimizing total cost. The software developed implementing this system is called RSUTAMS. RSUTAMS is generic in nature, employing a visual interface that allows users to customize it to suit their particular transit asset management database structure and practice through a series of models.</td></tr>
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GIS-BASED INTEGRATED RURAL AND SMALL URBAN TRANSIT ASSET MANAGEMENT SYSTEM

Project MTC-A-2

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EXECUTIVE SUMMARY

This study developed a methodology for improving the practice of making transit asset investment decisions at state departments of transportation (DOTs) and local transit agencies. The study made four major contributions to the state of transit asset investment decisions.

First, the report provides a review of the literature on the relationship between maintenance (preventive and corrective) costs and transit vehicle conditions, and it discusses its relevance to the vehicle conditions encountered in US transit agencies. The maintenance costs include both vehicle operating costs (i.e., fuel consumption, oil consumption, repair/maintenance, and depreciation) and non-vehicle operating costs (i.e., vehicle downtime due to maintenance work and road calls due to vehicle breakdowns on the road).

The majority of studies in this area find that there are significant differences in vehicle operating costs between road types (i.e., bituminous versus gravel versus earth), age, mileage, and vehicle type. Vehicle repair/maintenance costs are found to be primarily affected by vehicle condition. In terms of non-vehicle operating costs, vehicle downtime due to maintenance work and road calls due to vehicle breakdowns on the road were extensively studied in relation to vehicle condition.

The second contribution of the study is the development of a new vehicle deterioration model based on the ordered probit method. The major capability of the model is to predict the future conditions of the vehicle based on the historical records of the selected dependent factors, such as the vehicle's age, mileage, current conditions, and so forth. To best predict the vehicle's future condition, the most valuable dependent variables were identified.

The contribution of possible variables was analyzed and the factors that affect a vehicle's future condition were specified. The model can identify the relative importance of the independent variables with the given condition ratings. In addition, predictions can be made for individual vehicles or a group of vehicles at different condition ratings, both of which are important for the management system. Knowing the percentages of vehicles at different condition ratings in the future based on the present and historical conditions, a transit fleet manager can allocate the budget more efficiently and accurately.

The third contribution of this study is the development of relationships between vehicle conditions and the cost of preventive and corrective maintenance and a life cycle cost analysis (LCCA) methodology incorporating these cost relationships into network level and project level decisions. One can use these relationships and LCCA to select the best maintenance strategies for short- and long-term operation.

The fourth contribution of this study is to develop an integrated transit asset management system to incorporate the developed models described above and help managers make decisions about which applicable maintenance to use on the basis of minimizing total cost.

The system consists of the following modules:

1. Inventory

2. Condition assessments
3. Updateable prediction models for asset performance
4. Life cycle cost analysis
5. Maintenance action prioritization schemes and scheduling

The software developed for implementing this system is called RSUTAMS. RSUTAMS is generic in nature, employing a visual interface that allows users to customize it to suit their particular transit asset management database structure and practice through a series of models dealing with

- Transit management database descriptions
- Transit vehicle classifications
- Vehicle condition states
- New vehicles
- Corrective treatment performance
- Unit costs of transit asset for the agency
- Analysis

INTRODUCTION

Problem Statement

Asset management is a challenge faced by every transit system, large or small, in the four-state region. At the state level, transit officials are responsible for making policy and funding distribution decisions as they support local agencies and ensure that these systems run effectively and efficiently. At the local level, there are three major challenges to efficient and effective asset management. Managers must meet the challenges of the special service delivery design typical for rural and small urban systems. They must work within the financial constraints typical of many rural and small urban systems. Finally, any asset management plan must operate within the human resource capacity of the agencies to develop and maintain systems.

Rural transit systems are widely diversified with a variety of service delivery configurations offered in small cities, countywide, or multi-county service areas. The service delivery configurations may include fixed-route, point-deviation, demand-response, service routes, and downtown circulator, or special hybrids of these services.

The rural transit agencies face increased demand on their systems with limited resources. Managers must deal with system complexity and public demands for accountability and expectations regarding levels of service. With the growing demand from transit users for superior service regarding safety, comfort, convenience, and security, the high cost of capital assets for public transit systems has made effective transit asset management even more critical. Innovative technologies can assist transit managers in the challenge to make the best use of available resources and meet the needs of transit users. An integrated management system provides the tools needed by managers to make informed asset allocation decisions.

Managers of rural and small urban systems generally have limited human or technology resources for initial implementation of an on-going, comprehensive, and structured asset management system. The staffing generally is not available to consolidate stand-alone components from asset management. At the state level, an asset management system typically has not been feasible because system information from small transit operators often is not standardized and is difficult to collect. Small systems are just beginning to be automated, relying primarily on manual and intuitive management tools.

Research Objective

The objective of this research project was to develop a computerized asset management system for rural and small urban transit systems to help with capital improvements to existing transit assets, maintain the current level of service, and provide new assets, thereby improving and expanding service. Particular emphasis was placed on developing the methodology to incorporate into this system and developing a model for vehicle deterioration and life cycle costs. When feasible, live data from transit agencies was used to build the model. Further discussion regarding life cycle costs is presented in Appendix B.

Another project goal was to develop vehicle maintenance cost relationships and a methodology for incorporating agency costs into vehicle LCCA whereby

- Agencies costs are related to vehicle condition (i.e., key components), and
- Operation conditions (i.e., age, mileage) are related to vehicle condition.

While the issue of allocating assets between agencies based on agency performance and resources is important, it was not considered in this study.

Work Plan

An effective RSUTAMS requires accurate and efficient models for the prediction of asset conditions. The ability to form accurate forecasts has been highly valued throughout this project. RSUTAMS can make statements about future conditions of the vehicles and facilities and future actions to improve the condition.

Initially, a two-stage approach was proposed. The asset management issue would be explored at the state level during stage one and at the local agency level during stage two. This project was focused on stage two, examining allocation of resources within the agency closely.

To meet the objectives of this project, the following tasks were accomplished:

1. Conduct a literature search on asset management for transit systems
    a. Forecasting methodologies
    b. Maintenance costs
    c. Life cycle cost model
2. Assemble and convene project advisory committee
3. Develop asset management system requirements
4. Develop an asset management model
5. Data collection

LITERATURE REVIEW

The Intermodal Surface Transportation Efficiency Act of 1991 (ISTEA) requires the United States Department of Transportation (US DOT) to issue regulations on the development and implementation of six management systems, including a system for managing public transportation facilities and equipment. ISTEA requires that the results of the management systems be considered in making decisions under the Federal Transit Act, which provides authorizations for highways, highway safety, and mass transit for the next six years. This plan covers the management of existing assets, which includes maintaining, monitoring and improving transportation system performance. Many of the provisions originated in ISTEA have been continued or expanded in its follow-up legislation, the Transportation Efficiency Act for the 21st Century (TEA-21). According to TEA-21, the purpose of funding the Rural Transportation Accessibility Incentive Program is to help public and private operators finance the incremental capital and training costs of complying with the DOT's final rule on accessibility of over-the-road buses. To monitor vehicle conditions, measure performance, predict future deterioration trends and allocate budget more effectively, the state and local agencies need a decision making tool.

In 1998, the Federal Highway Administration (FHWA) established the Office of Asset Management. It works closely with the American Association of State Highway and Transportation Officials (AASHTO) to provide technical assistance to help state transportation agencies to implement the Asset Management System (AMS) nationwide.

Since the physical assets are deteriorating day by day, to ensure high-quality service while facing limited staff resources, state and local agencies turned to AMS to find cost-effective solutions. In June 1999, the Governmental Accounting Standards Board (GASB) issued statement No. 34, "Basic Financial Statements for State and Local Governments," which requires state and local governments to expand the information provided in their annual financial statements. The GASB 34 includes all capital assets and long-term liabilities and recommends government agencies establish transportation infrastructure values in reporting capital assets as part of their financial statements. The GASB 34 also pushes the state and local agencies to create and use AMS.

The Interim Final Rule (IFR) on Management and Monitoring Systems, issued jointly by the Federal Transit Administration (FTA) and FHWA, states that a Public Transit Management System (PTMS) is "a systematic process that collects and analyzes information on the condition and cost of transit assets on a continual basis. It identifies needs as inputs to the metropolitan and statewide planning process, enabling decision makers to select cost-effective strategies for providing and maintaining assets in a serviceable condition." PTMS's major function is as an informational tool for making investment decisions about the existing transit assets. "Asset management," as defined by Office of Asset Management, FHWA, is a business process and a decision-making framework that covers an extended time horizon, draws from economics as well as engineering, and considers a broad range of assets [1].

In 1994, FTA published the transit condition ratings from 0 (the worst condition) to 4 (the best condition), as shown in Table 1, to standardize the transit vehicle evaluation. Thereafter, new methodologies were introduced to fit the discrete ratings. A literature review of forecasting methodologies and consideration of maintenance costs is presented as follows.

Table 1. Rolling-stock condition ratios (FTA 1994)

Condition	Description
0 - Bad	In sufficiently poor condition, continued use presents potential problems.
1 - Poor	Requires frequent major repairs.
2 - Fair	Requires frequent minor repairs or infrequent major repairs.
3 - Good	Requires only nominal minor repairs.
4 - Excellent	Brand new, no major problems exist.

Traditionally, rural and small urban transit agencies have approached the maintenance and operation of transit system with a crisis-based approach due to shortage of financial support, maintenance staff, and maintenance equipment. As a result, the impact of important considerations such as operation duration and service quality, life cycle costs, environmental impacts, and safety requirements are not fully explored. State and local transit agencies are frequently faced with budget shortage problems. Due to limited budget and financial support, fleet managers turned to management systems to achieve high returns on the constrained investment. However, there are several problems in development of an efficient and effective management system, including 1) multiple, often conflicting objectives; 2) uncertainties related to asset future conditions future decisions; 3) Lack of qualitative and quantitative data.

Forecasting Methodologies

A systematic approach for the determination of deterioration of transit assets and an integrated transit asset management system are necessary to fully understand the transit asset system status.

To predict the asset deterioration condition based on the historical and current inspection data, some common regression approaches were developed, such as a linear regression method and Markov chain transitional probability matrix method. Many pavement management systems use the linear regression approach for estimating the future condition of pavements while the Markov chain transitional probabilities are widely used in bridge management systems. Each approach has advantages and disadvantages. However, neither fit the requirements for estimating the deterioration of a transit fleet of vehicles.

Schaevitz [3] described a straight-line depreciation model to valuate the capital asset. The residual value of a vehicle was directly proportional to the years of life remaining. The advantage of the method is that it is simple and easy to use. However, in reality, the depreciation trend is based on a number of variables, not just the years of life remaining. Therefore, it cannot predict accurately the qualitative and quantitative relationship between capital asset deterioration and various independent variables. In addition, the linear regression approach requires the condition states to be continuous. Such an assumption is not appropriate since the condition states are ordered and discrete.

Jiang, and Sinha [4], with Saito [5], proposed to use Markov Chain model to predict the bridge condition ratings, which is assigns 1 as worst and 9 as best . The Markov chain method was developed to find the relationship between condition rating and bridge age. The advantage of the Markov chain model is that the probabilities of a bridge condition transitioning from one state to another for a given time span can be determined. Moreover, service life prediction by Markov chain has the advantage over the statistical regression approach in that it can be used not only to estimate the average service life of a number of bridges, but also the service life of any individual bridge. However, the regression based Markov chain approach is not suitable for modeling deterioration because it suffers from various limitations. For example, the Markov chain method could not explicitly link deterioration to more than one explanatory variable at a time. It has to classify bridges into different categories to eliminate the side impact of other explanatory variables such as traffic volume and climate. Another assumption, which is not appropriate either, is that the bridge condition rating would not drop by more than 1 rating level in a year. Thus, the bridge condition would either stay in its current rating or transition to the next lower rating in a year. Therefore, it could not predict the future probabilities of the bridge being in any condition ratings.

Ludwig [6] presented a deterioration model for the New Jersey Transit Public Transportation Facilities and Equipment Management System. This model introduced the rolling stock rating conditions from “1” (the excellent condition) to “5” (the worst condition), which provided a qualitative way to evaluate the rolling stock status. The model estimates the future condition of each individual transit asset and reflects the changes from one condition state to another over time. The deterioration rates are the median years to transit from one condition state to another. The transitional probability is calculated from the following formula:

$$p = 1 - \exp[\frac{1}{median\ years} \times \ln(0.5)] \qquad (1)$$

In addition, the model introduced the transitional probability of transit assets from one condition state to another over a one-year period. It uses different median years for different types of transit assets as input of equation (1) to get the probabilities, which reflects the dynamic demand of different transit assets. Nevertheless, the probabilities did not change from one year to the next and therefore do not reflect the real dynamic nature of vehicle conditions. Obviously, if a vehicle was well maintained last year, its probability of changing to the next condition state will decrease.

The advantage of the model is that it recognized that the different parts of a vehicle should have different deterioration rates. For instance, it classified the transit bus into electrical, interior and exterior parts and estimated each attribute’s deterioration rate separately and added them up together to get the final overall deterioration ratings. In addition, the model estimates an asset’s remaining useful life based on inspected actual conditions instead of only the vehicle age.

The weakness of the model is that it did not consider that maintenance activities might extend or shorten the vehicle life. However, it did recognize the overhaul effect and is able to recognize the better condition state of a vehicle once overhauled.

Karlaftis and Sinha [7] developed an Ordered Probit (OP) model to predict the deterioration of transit rolling-stock for the Indiana Department of Transportation (INDOT). In their research, they adopted FTA's vehicle ratings ranging scale from 0 (the worst condition) to 4 (the best condition), shown in Table 1, which is similar to Ludwig's rating. It not only recognized the discrete ordinal property of the dependent variables, the 0 to 4 ratings, but also the linked deterioration with explanatory variables such as age, mileage, weather and engine-rebuild history. Two models were developed, one for busses belonging to a large transit system and another for busses belonging to smaller transit systems. Average probability was calculated for potential use on similar buses with alternative operational and maintenance policies. The advantage of doing this is that their approach can estimate the maintenance costs for the next time period more accurately. However, the aggregate probabilities made it hard to predict each individual transit vehicle's condition state in the upcoming time period. In addition, because of the lack of the time value in the codes for maintenance history by FTA (1994), shown in Table 2, and the difficulty of collecting maintenance data, only engine-rebuild history was considered in the model. Further, Karlaftis and Sinha mentioned environmental factors, such as climate and weather, but it is hard to quantify them. However, the result is still quite useful. The method was introduced in many practical situations, for instance, optimal timing for bus replacement and life cycle analysis.

Table 2. Codes for maintenance history (FTA 1994)

Maintenance Code	Maintenance History
1	Minimum maintenance
2	Normal corrective maintenance
3	Corrective maintenance
4	Major corrective maintenance

Karlaftis [8] improved the model so it could forecast vehicle condition states at both the aggregate (the whole fleet) and disaggregate (individual vehicles) levels. The Ordered Probit (OP) model, which is similar to the one presented by Karlaftis and Sinha [7], was proposed for use at the aggregate level. For the disaggregate level, the Discriminate Analysis methodology was introduced to estimate each individual vehicle's future condition state. It is a multivariate statistical method concerned with assigning observations to previously defined groups. It takes the same input parameters, such as age and mileage. By using a linear combination of the parameters in each condition state, the method can predict the next condition state of each individual vehicle, when the latent vehicle surveyed variables are known. This simple and relatively accurate method provides a possible scenario analysis for each individual bus regarding the condition states under different driving policies. The overall prediction accuracy of the discriminate method is relatively high.

Maintenance Costs

There are many other independent variables related to the prediction of the vehicle's deterioration model. Maintenance cost is one of the most important variables that affect the next condition state and the financial budget. It may also be the most difficult data to collect.

Peskin [9] presented an approach to estimate the maintenance budget for the rail transit. To project capital rehabilitation and replacement (R&R) costs for rail transit assets, the rail assets were classified into several classes. The following equation was applied to each asset class to estimate the annual cost:

$$\text{R\&R Cost} = \text{Original asset value} \times \text{Inflation factor} \times \text{R\&R cycle} \tag{2}$$

The inflation factor is the documented historical inflation rate provided by Washington Metropolitan Area Transit Authority Office of Program Control. The R&R cycle is briefly shown in Table 3. The final R&R cost of the rail transit is the summation of the net present value of all the estimated R&R costs of each asset class. When estimating the R&R cost for rail vehicles, the average cut-off number was 353,000 dollars per car.

Table 3. R&R cycles

Cycle Length	Percentage of Current Asset Value
10 years	0.5%
20 years	1.0%
30 years	1.5%

While representing improvements over R&R cost, the approach is still subject to several limitations. For one thing, it is hard to estimate the future inflation rate to calculate the Net Present Value. This method introduced a potential possible error due to the estimation of inflation rate. In addition, the equation cannot reflect the condition of each individual vehicle or a sub-group of vehicles. It is an average estimation. Since Peskin presented this paper in 1988, no feedback information was available. Therefore, one cannot tell how accurate the method was. Further, the equation cannot accurately and dynamically predict the future cost.

However, the Peskin presented several valuable considerations. Classifing the vehicle into several major parts to evaluate the maintenance cost is a valuable approach. In our research, one can define the vehicle's cooling system, transmission system and engine related system into separate categories. However, it is very time-consuming and costly method of data collection.

Following the FTA's standards about the condition state of a vehicle rated from 0 to 4, experts estimated the vehicle's condition state by observation. In addition, major accidents or other incidents repair costs were considered as part of the maintenance cost in our approach.

Schaevitz [3] also described an approach for estimating maintenance cost in his paper. The maintenance cost is divided into two parts, fixed cost and variable cost. The fixed cost does not change each year while the variable portion was predicted to increase at 6 percent rate based on the historical maintenance data. For vehicles considered in this project, the fixed maintenance cost includes the basic routine maintenance cost, such as oil change expenses. But the variable cost estimate, increasing 6 percent each year, is not accurate since different categories of vehicles have different unpredictable maintenance costs every year, such as accident recovery costs. Therefore, it cannot reflect the dynamic real conditions of each vehicle. The advantage of the Shaevitz method is that after each scheduled overhaul, the car would run better and its maintenance cost would decrease. In other words, the vehicle's condition state moves to better state rather than remain in the current or lower state. Nevertheless, the method for estimating the result of overhaul was inaccurate. For example, if a vehicle was overhauled in its seventh year, the maintenance cost in the following year may equal its cost in its third year. An advantage to this method is that the future costs were discounted to reflect the time value of money.

Life Cycle Cost Model

A well-designed integrated Transit Asset Management System (TAMS) should include transit asset condition assessments, a well-defined condition rating system, updateable prediction models for asset performance, life cycle analysis, and development of prioritization schemes for selecting maintenance/repair options. The Rural and Small Urban Transit Asset Management System (RSUTAMS) can play a key role to monitor and optimize the preservation, upgrading, and timely maintenance of the transit system, more specifically, the vehicles and other fixed assets, through cost-effective management, programming, and resource allocation decisions. It's a decision-support tool developed to assist Kansas state and local transit agencies in determining how and when to make investments on vehicle and other fixed assets to maintain or improve the existing asset, identify current and future deficiencies, estimate the backlog of investment requirements, and predict the future requirements of the upcoming fiscal year.

RSUTAMS serves as one of the principal means by which the transit agencies can develop innovative near-term or long-term solutions to meet mobility, environmental, and energy objectives. Because it uses optimization techniques to obtain minimum cost of maintenance/repair strategies over the life cycle of transit system, the 'what-if' analysis in this system will help the fleet managers to make more cost-effective decisions about maintenance (repairing, overhauling, or replacing) of vehicles to make the best use of each dollar and continue to receive adequate funding. By taking into account future conditions as a consequence of present maintenance/repair actions, the best action, priority, and schedule can be determined.

PROJECT ADVISORY COMMITTEE

The project team assembled an excellent advisory committee with a wide range of experiences. The members of the Project Advisory Committee are listed in Table 4.

Table 4. Project advisory committee members

Contact	Agency	Title
Marcia Bernard	KCK The Bus	General Manager
Bob Bourne	Ames Transit Agency	General Manager
Mike Floberg	KDOT	Asst ITS Coordinator
Georgia Janssen	Nebraska Association of Transportation Providers	Executive Director
Rose Lee	RIDES	Executive Director
Valerie Miller	Ray County Transportation Initiative	
Karin Rexroad	City of Lawrence Transit	Transit Manager
Ron Straight	DSNWK, Inc.	Executive Director
Janice Turner	Metro Area Paratransit System	Transit Coordinator
Jim Van Sickel	KDOT Office of Public Transit	Program Manager
Matt Volz	KDOT Bureau of Transportation Planning	ITS Coordinator
Lind Yaeger	Oats, Inc.	Executive Director

Approximately 10 of these panel members met with the project team on August 22, 2000, in Kansas City. The agenda for the meeting is presented in Table 5.

Table 5. Agenda of project advisory committee meeting

Agenda item	Details
Introduction of Project Team and Advisory Council Members Project Objectives and Problem Statement What are GASB 34 and Asset Management? Existing Asset Management Systems	
Working Session	Asset Management Needs of Non-Urban Transit Systems Inventory Management Resource Management Needs Prediction Model Routing and Scheduling Software Environment Hardware Requirements
Summary and Conclusion	

After a general discussion of the project and GASB 34, the majority of the time in the meeting was spent in the Working Session on what would be useful to a rural or small urban transit system. In general, the group very quickly came to the conclusion that the system should operate in the Windows environment with a standard hardware configuration. The group also decided that demand forecasting was to have a lower priority. Since geographical information systems (GIS) was included in the project title in order to allow for demand forecasting, it was the consensus of the group that it did not need to be included until the demand-forecasting module was developed.

There was a consensus among the group that an asset management program would be of interest to the panel members and would be a benefit to the agencies they represented if it could justify expenditures for routine maintenance. The panel members volunteered to provide data to the project team required to build the models.

ASSET MANAGEMENT SYSTEM REQUIREMENTS

After a review of the existing asset management systems for transit systems, it was determined that the majority of existing systems required too much data and software systems that were too sophisticated for the majority of small urban or rural transit system. As the project team learned, the majority of the panel members are too busy providing rides and or could not provide the data required to support an asset management system.

The project team came up with four requirements for an asset management system for small urban and rural systems:

1. The system should be in the Windows environment and Microsoft Access was the preferred database management system. Visual Basic linked to an Access database would be a desired alternative. For an asset management system to be practical for small urban and rural transit agencies, it must be written for the microcomputer environment.

2. The system should contain a method for tracking maintenance costs. Initially, it was decided that the system should not connect the maintenance module directly to the analysis system. Until there is confidence in the model, it is more desirable for a manager to check the computer-generated information before it is incorporated into the model.

   To meet this requirement, the creation of an electronic service manual was proposed. For each vehicle type and model, the asset management system should be able to support the required vehicle systems. For example, each vehicle might have the following systems:

   - Routine lube, oil, filter
   - Engine
   - Transmission
   - Electrical
     - Cooling
     - Body
     - Tires
     - Lift and other customized systems, etc.

   For each of these systems, the service intervals, mileage and time, are defined. As the mileage is recorded on a regular basis, the system should flag the operator when service activities are necessary. As these service activities are completed, the mileage and service date is recorded. The expenses associated with these activities should be stored and broken down by parts, labor, and miscellaneous. Other desirable features would include processing of work orders, accounting tools, etc.

   The system needed a way to track present and future conditions of the vehicle fleet. There needs to be a system to define the condition states and future conditions based on vehicle parameters.

3. It became readily apparent that the data collection of vehicle parameters was going to be rather difficult. Small urban and rural agencies focus on their mission of providing rides to people and not on operational statistics. For example, vehicles driven on gravel roads are known to deteriorate faster than vehicles driven on paved roads. While agencies can estimate that 30 percent of their mileage is on gravel roads, they have no way of telling how many miles of gravel roads a particular vehicle traveled.

   Building the methodology to collect the present condition of vehicles turned out to be a more difficult project than expected. The first issue was what variables should be requested. The project team developed a spreadsheet of the requested information.

4. The system needs to include a means for inputting budget information and then be able to conduct a life cycle cost analysis.

Each member of the panel was asked to discuss the type of input data required to conduct the life cycle cost analysis.

Decision Making with Probabilities

In the vehicle maintenance/replacement decision-making situation, the development of the ordered probit model made it possible for the decision maker to know enough about the future condition states by estimating probabilities of the occurrence of future vehicle condition states. Given that probabilities can be estimated, expected opportunity gain decision criteria is selected to aid the decision maker in making short-term decisions. The basic steps to carry out the decision making with probabilities include the following:

1. Estimate the transition probabilities of vehicle condition state using OPM.

2. Calculate the expected opportunity gain.

3. Select the alternative with the maximum ratio of expected opportunity gain and maintenance cost.

The probabilities from one condition state to another condition state are similar to posterior probabilities computed using the ordered probit model. These are the transition probabilities of the vehicle condition states given a vehicle's current condition and the maintenance activities performed on it. Note that the decisions from the expected opportunity gain are totally dependent on the probability estimates (predictions). Thus, if inaccurate probabilities are used, erroneous decisions will result. In other words, if the predictions from the deterioration model are inaccurate, erroneous decisions will result. Therefore, it is important that the deterioration model be as accurate as possible in determining the probabilities of each condition state.

When such probabilities are calculated, the expected opportunity gain approach can be used to identify the best decision alternative. Let's first define the expected opportunity gain of a decision alternative and then show how it can be used for the vehicle maintenance problem. Let

N = the number of condition states of a vehicle

$P(cs_{ij})$ = the probability from condition state i to j

Since one (and only one) of the N condition states of a vehicle can occur, the associated probabilities must satisfy the following two conditions:

$P(cs_{ij}) \geq 0$, for all condition states

$\sum_{j=1}^{N} P(cs_{ij}) = 1,\ i = 1,2,3,4,5$

The expected opportunity gain (EOG) of decision alternative is defined as follows:

$$EOG(d_{ik}) = \sum_{j=1}^{N} P(cs_{ij})\, R_{ij}$$

The expected opportunity gain of a decision alternative is the sum of weighted extended life years for the decision alternative. The weight for the extended life of a vehicle is the probability of the associated condition state and therefore the probability that the transition occurs from condition state i to j.

The expected opportunity gain approach evaluates each decision alternative in terms of its expected opportunity gain. The recommended decision alternative is the one that provides the best-expected opportunity gain. In order to apply the concept of expected opportunity gain as a decision-making criterion, the decision maker must first estimate the probability of occurrence of each condition state. Once these estimations (predictions) have been made, the expected opportunity gain is computed by multiplying each outcome by the probability of its occurrence, and then summing these products.

In this case, extended vehicle life due to various actions of maintenance/repair on a specific vehicle is the decision criterion of expected opportunity gain . As with the maximizing gain criterion, the best decision results from maximization of the benefit/cost ratio. The extended life is the primary benefit associated with applying a maintenance/repair action to a specific vehicle (e.g. rebuilding an engine to prolong a bus life 4 years), and the cost is the actual maintenance/repair cost. To use this criterion, we multiply the probabilities by the extended life gain for each decision outcome and summarize the products to get the expected opportunity gain, and then divide the expected opportunity gain by the associated M/R cost. The benefit/cost ratio is represented by

$$Ratio = EOG(d_{ik}) / COST_j$$

The calculations required to identify the decision alternative with the best expected value can be conveniently carried out on a decision tree. A decision tree is a graphical diagram consisting of decision nodes and branches, and represents the sequence of events in a decision situation. The branches emanating from a decision node reflect the alternative decisions possible at that point. Figure 1 shows the decision tree as an example for vehicle maintenance problem with condition state branch probabilities.

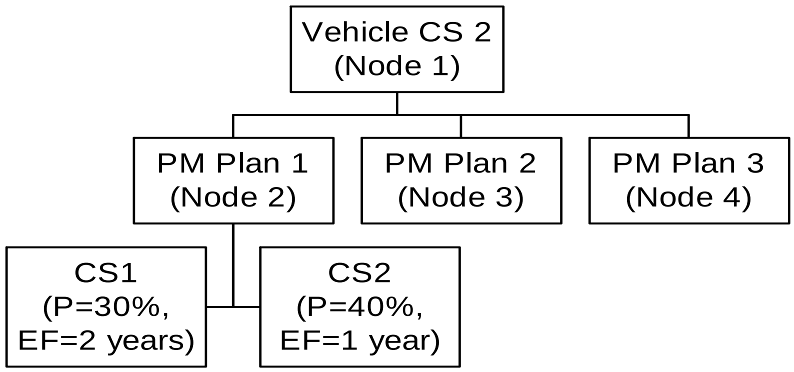

Figure 1. Decision tree

To see how the decision tree analysis is conducted, consider the result at node 1 first. Node 1 signifies a decision to select a PM plan from the three alternatives. The boxes on the second layer are PM plan alternatives in dollars, and the branches emanating from them indicate the condition states that may occur: excellent, good, fair, bad conditions. Determining the best decision involves computing the expected opportunity gain at each probability node on layer three.

Working through the decision tree, we first compute the probabilities using the ordered probit model given alternative PM cost. Then we compute the expected opportunity gain at each alternative node. We weight each possible transition at each alternative node. By doing this, we obtain the expected values for nodes 2, 3, 4, and 5 as shown in Figure 1 above. An expected opportunity gain of the extended life can be computed at each probability node.

Each of these three expected opportunity gains at nodes 2, 3, and 4 is the outcome of a possible decision that may occur. The node corresponding to the highest opportunity gain, is from node 1 to node 3. This path represents the decision to alternative PM plan 2.

Deterioration Model

An effective RSUTAMS requires accurate and efficient models for predicting transit asset conditions. The prediction models are imperative for a complete RSUTAMS. Various statistical methods and techniques for asset deterioration prediction, such as the linear regression method or Markov chain method, have undergone development in the past two decades. They have been widely used to predict the asset deterioration condition based on the historical and current inspection data.

Since future vehicle conditions involve uncertainty, the approach for the prediction is a statistical one. In this research, we hypothesized that the combination of age, mileage, maintenance cost, road condition, and traffic volume were related to vehicle state conditions, while model fitness might be better if more history conditions were included. For a particular vehicle within a vehicle group,

$$\text{condition state} = f\,(\text{age, mileage, M/R cost, etc.}) \tag{3}$$

Important features of the dependent variable in (1) are that it is discrete and that it could be characterized as ordered. Condition state is discrete because it can only take on a limited number of integer values. It could be considered as ordered because a vehicle condition has several condition states from good to bad. These features suggested the ordered probit model (see Greene 1990) as a possible method for estimating the relationship shown in Equation (3).

The ordered probit model assumes the existence of a continuous, unobserved variable underlying an observed categorical variable. As Table 1 illustrated, the data collected about the vehicle conditions are categorical variables. It appears to be more appropriate for a problem in which the dependent variable of interest is the unique choice made from a set of distinct alternatives. Categorical variables are those for which the measurements are not so clearly defined in quantity, rather measured using only a limited number of values or categories, such as “good,” “fair,” or “bad.” In our case, a vehicle can be identified as a “brand new,” “small damage,” or “severe damage” vehicle. Categorical variables are classified into nominal and ordinal. If the category has natural order, such as “compact car,” “midsize car,” or “luxury car”, it’s called ordinal. Otherwise, it’s called nominal.

Important issues to considered when modeling vehicle condition included the selection of explanatory variables, initial hypotheses as to how these variables are related to vehicle condition, and how to measure modeling success. In general, because vehicle condition state is measured according to a vehicle’s inside and outside defect condition, number of road calls, and maintenance history, it is reasonable to assume that factors affecting these variables would adequately explain vehicle condition.

Different thresholds are defined in the model to classify the categories. Ordinal variables clearly order the categories, but absolute distances between the categories are unknown or not clearly defined. An interval variable is one that does have numerical measurements between any two adjacent categories. The probability of vehicle condition was named P(vc). As the name suggests, the probability is intended as the independent variable in the development of relationships between vehicle condition and agency cost components (e.g., vehicle maintenance/repair cost, tire cost and so on). The OPM is briefly described as follows:

$$y^*_i = \beta\,' X_i + \varepsilon_i \ ,$$

where

y^* is the dependent variable (the vehicle's condition ratings)
β is the vector of estimated parameters
X is the vector of explanatory variables
ε is the normally distributed error term

Parameter i indicates the observations, y is an unobserved, latent dependent variable. X represents the selected observable independent variables, such as vehicle's age, cumulative mileage, percentage of paved road, maintenance costs, etc. Parameter β is a set of unknown coefficients, which represent the effect of explanatory variables, X, on underlying condition states. Only the signs, relative magnitudes and significance of the parameter estimates (β) can be interpreted directly. Parameter ε is normal distributed random error with a mean zero and variance one.

Instead of observing y^*, we observe a censored version of y^*, consisting of one of several discrete values defined by FTA (1994) in Table 1. An individual y^* falls in category n if $\mu_{n-1} < y^* < \mu_n$. The vehicle condition state y is related to the underlying latent variable, y^*, through thresholds μ_i, where i=0,1,..,4.

$$
\begin{aligned}
y &= 0 \quad iff \quad & y^* &\le \mu_0 \\
y &= 1 \quad iff \quad & \mu_0 < y^* &\le \mu_1 \\
y &= 2 \quad iff \quad & \mu_1 < y^* &\le \mu_2 \\
y &= 3 \quad iff \quad & \mu_2 < y^* &\le \mu_3 \\
y &= 4 \quad iff \quad & \mu_3 < y^* &
\end{aligned}
$$

The μ's are unknown threshold parameters separating the adjacent categories to be estimated with β. According to Greene (1999) [10], we have the following probabilities:

$$
\begin{aligned}
Pob\,(y=0) &= \Phi(\mu_0 + \beta'X) \\
Pob\,(y=1) &= \Phi(\mu_1 + \beta'X) - \Phi(\mu_0 + \beta'X) \\
Pob\,(y=2) &= \Phi(\mu_2 + \beta'X) - \Phi(\mu_1 + \beta'X) \\
Pob\,(y=3) &= \Phi(\mu_3 + \beta'X) - \Phi(\mu_2 + \beta'X) \\
Pob\,(y=4) &= 1 - \Phi(\mu_3 + \beta'X)
\end{aligned}
$$

Where Φ is the notation of the standard normal cumulative distribution function (cdf). To keep all the probabilities to positive,

$$0 < \mu_0 < \mu_1 < \mu_2 < \ldots < \mu_3$$

Usually, the maximum likelihood method is used to obtain the estimated values of μ's and β's. The likelihood function is defined as follows.

$$
L(y) = \sum_{k=1}^{m} \Big\{ CS_{1k} \times \log \Phi(\mu_0 + \beta' X) + \sum_{i=1}^{3} \{CS_{ik} \times \log[\Phi(\mu_i + \beta' X) - \Phi(\mu_{i-1} + \beta' X)]\} + CS_{4k} \times \log[1 - \Phi(\mu_3 + \beta' X)] \Big\}
$$

Where CS_{ik} (condition state) is an indicator variable that takes on the value of one if the realization of the k*th* observation y_k's condition state is i, and zero otherwise. Parameter m is a constant that represents the total number of observed vehicles. Once the likelihood function is formed, the estimation of the unknown parameters μ's and β's can proceed.

As mentioned before, the impact of a change in an explanatory variable X on the estimated probabilities of the condition ratings is unequivocal. For example, if β_j is positive, an increase in the value of X_j will decrease the probability of changing to condition state 0 but increase the probability of changing to condition state 4. However, the impact on the estimated probabilities of intermediate condition ratings can be in either direction. An estimated β value does not estimate the change in the probability of a condition state due to a unit change in the relevant explanatory variable.

$$\frac{\partial \ln L(\beta, \mu)}{\partial \beta} = \sum \frac{\partial \ln Pob(y = y_i)}{\partial \beta} = 0 \text{ ,}$$

where y_i = 0, 1, … , 4.

Each of the selected variables may have ambiguous effects on vehicle condition. Functional form is determined by the dependent variable and by hypothesized relationships between it and explanatory variables. Many measures of data fitness to discrete dependent variable models have been developed (see Greene [1990] for descriptions of a few). An obvious and common measure is the percentage of correct predictions. This can be compared to the percentage of correct predictions obtained using some naive model (e.g., sample proportion for each grade). Combining these two, we have the increase in absolute percentage of correct predictions. Call this the fitness improvement index (FJI).

Other measures of success in maximum likelihood involve likelihood criteria. One is the likelihood ratio test, with the criterion distributed chi-squared (k-l). This essentially tells whether the right-hand-side variables significantly explain any variation:

x~=-2(lnLo-ln.L) (7)

where z is the log-likelihood of the estimated equation and L, is the log-likelihood of a model with only the intercept on the right-hand-side.

Overview of Data Collection Needs

The first activity under this task was to define the vehicle types. It was decided that for small urban and rural systems, guidelines found in *TCRP Report 61, Analyzing the Costs of Operating Small Transit Vehicles* were appropriate. Basically, the categories of vehicles listed are found in Table 6.

Table 6. Categories of listed vehicles

Category	Description
1	Van
2	Van Cutaway, Single Wheel
3G	Van Cutaway, Dual Wheel, Gasoline
3D	Van Cutaway, Dual Wheel, Diesel
4	Purpose Built, Front Engine
5	Purpose Built, Rear Engine
6	Medium Duty, Low-Floor Front Engine
7	Heavy-Duty, Low-Floor Front Engine
8	30-Ft, Heavy-Duty Bus

A more detailed description of each vehicle category can be found in Appendix A. Obviously, each of these vehicles will have a different deterioration model and life expectancy. This would need to be considered in the development of the deterioration model. Also, one would not expect to find all of these vehicle types in small urban and rural systems.

As part of the development of the deterioration model, condition states for each vehicle had to be defined. Again, it was thought that a verbal description was the desired format. It was also decided to keep it simple and use an existing standard. Therefore, the approach used by FTA was selected for this study and is listed here as Table 7 for convenience.

Table 7. Rolling-stock condition ratios (FTA 1994)

Condition	Description
0 - Bad	In sufficiently poor condition, continued use presents potential problems.
1 - Poor	Requires frequent major repairs.
2 - Fair	Requires frequent minor repairs or infrequent major repairs.
3 - Good	Requires only nominal minor repairs.
4 - Excellent	Brand new, no major problems exist.

As part of the final step in developing the deterioration model, the factors that could influence the vehicle condition had to be defined. For this study, the following parameters were selected:

- Vehicle mileage
- Vehicle age (months)
- Vehicle type
- Percent of mileage driven on paved roads
- Maximum vehicle (passenger) capacity
- Passenger volume (number of passengers carried)
- Maintenance expenses

Maintenance expenses were broken down into the following categories: Routine preventive maintenance (PM) and corrective maintenance (CM). Routine preventive maintenance included all normal maintenance expenses such as oil changes, tires, lubrication, and all normal day-to-day maintenance activities. Corrective maintenance covered all expenses that were not preventive in nature, the remainder of the maintenance expenses. The project team recommended that corrective maintenance expenses be broken into the following categories:

- Engine related
- Cooling system
- Transmission
- Electrical system
- Brake
- Body improvements
- Other

Other variables were considered but were not selected. For example, weather could be an important variable because of the degree of salt used on the roads. However, it was not considered because the study was focused on a single region.

Not all of the variables listed above were eventually included in the proposed deterioration model. Some were eliminated for two reasons. 1. The project team could not get the data that would allow for the discernment of that variable, or 2. some variables were found to be statistically insignificant. For example, the percent of mileage driven on paved roads could be an important variable but was impossible for any agency to determine on a per vehicle basis. While they could estimate that 30 percent of their mileage was on gravel roads, they could not determine how many gravel miles each vehicle was driven.

With the list of potential variables defined, the project team sent out a letter and spread sheet to ask for data. A follow-up phone call was made to each advisory panel member requesting that they respond to the questionnaire. Unfortunately, only two agencies responded. One agency had just started its operation, so all of its vehicles were brand new with little mileage. Fortunately, the other agency had a significant number of vehicles with a wide variety of conditions. In addition, some maintenance information was available.

Data Collection

Survey forms were sent to a number of transit agencies in FHWA Region 7, to collect fleet maintenance activities, associated costs, vehicle service time, mileage, capacity, passenger volume and percent of paved road. Each agency had between 1 to 50 vehicles to be classified into eight categories based on the vehicle’s weight, dimension, capacity and engine type. The classification standard is listed in Appendix C. The survey form and the raw data that were collected are presented in Appendix D.

While numerous contacts were made, vehicle data were received from one agency, Oats, Inc. Oats, Inc. is a transit agency providing rural public transit services in Columbia, Missouri. This agency provided information based on the vehicle's current operating condition and available recorded historical maintenance activities. The data set provided by Oats, Inc., contain vehicle service life, mileage, maximum passenger capacity, PM and CM costs from 1988 to the first quarter of 2001. The vehicle condition states assigned by experts were based on their best estimation following FTA's definition.

The vehicle database collected involved data for a total of 200 vehicles, but the actual sample size analyzed was limited to 63. Only data for older vehicles were analyzed (i.e., model year 1998 and earlier) to exclude newer vehicles for which repairs could have been covered under warranty and hence, omitted from the company expense records. As described later, the effect of vehicle mileage/model year on the cost of maintenance/repair was studied. A complete description of the data collection and analysis is given in next section.

A set of vehicle parameters expected to influence the vehicle condition states was selected. These parameters included: vehicle age, mileage, maximum passenger capacity, passenger volume, environmental factor and percent of paved road. Vehicle's age, in months, describes the age of the vehicle. Mileage shows how many miles the vehicle was driven. Annual maintenance cost gives an account of how much was spent to maintain it. Maximum passenger capacity is the maximum number of passengers a vehicle can carry at a time. Passenger volume describes how many passengers it carried in each study time interval. The environmental factor explains the impact of weather on those vehicles, and percent of paved road accounts for the percentage of paved road it drives on. There are some common sense and general study directions adopted in this research.

Data Analysis

This section presents analysis of field data followed by OP prediction and model calibration. Through the study, critical predictors were identified and plausible accuracy was achieved. To increase prediction precision, more data is essential.

Variable Selection

There are some common sense and general study directions adopted in this research. Before building a regression model, it is important to develop an intuitive basis for the model to explain how the possible explanatory variables might affect plausible outcomes. For instance, as the vehicle ages, the vehicle condition would deteriorate. However, that may not always correct. The future condition state also depends on other factors such as maintenance policies and costs. If a vehicle had a major overhaul in a study period, its condition state should be better in the following period. Mileage plays a similar role as age. The more mileage the vehicle has driven, the worse condition it is when all other factors are similar.

Vehicle capacity is another variable worth considering. Generally, the more passengers a vehicle can carry, the longer it lasts. For example, buses have a relatively long life cycle compare to mini-vans. However, the collected vehicle passenger capacity may not reflect the real condition since the owner can change the vehicle interior to provide more or less capacity. In the same category of vehicles, the maximum passenger capacity should be a constant. Since the analysis was conducted on vehicles in Category 2, single wheel vans, the maximum passenger capacity was always constant. Therefore, the impact of maximum passenger capacity was not considered further.

Another factor affecting the vehicle condition rating is the passenger volume in a given time span. The passenger volume is the number of passengers a vehicle carries in a given time interval. Usually, vehicles carrying more passengers per month deteriorate faster than those that carry fewer passengers, assuming all other conditions are identical. Unfortunately, the field data lacks information related to passenger volume. Therefore, further available data are essential to determine how significantly passenger volume affects vehicle condition states. The age, mileage, capacity and maintenance cost are the internal factors that affect vehicle deterioration process.

Possible external factors considered are environmental and pavement effects. However, environmental conditions, such as weather, were not explicative variables because there was no environmental condition data available. Pavement condition was also considered in this study. However, agencies could not document the number of miles traveled by each vehicle on gravel roads. Therefore, while we wanted to consider it, it was not possible. The data set from Oats, Inc., shows that the whole fleet runs on 65 percent of paved road and 35 percent of gravel road. Since the percent of paved road is constant, it does not have any impact on the condition ratings. Hence, it was removed from the explanatory variable list.

Quantify Selected Variables

Since the time interval of the data collected was in months, the vehicle ages are integers. Mileage is the accumulated distance that a vehicle ran until its mileage was checked. There is no hidden mileage. If the engine was overhauled or rebuilt, the mileage consecutively grows instead of starting from zero.

Maintenance cost was difficult to estimate. Vehicle maintenance cost was divided into two major categories, routine preventive maintenance cost and additional maintenance cost. Routine maintenance, which is also referred to as PM, includes all the activities listed in a vehicle maintenance manual. Those maintenance activities listed in the manual should be conducted after the vehicle was driven for a certain number of miles or a period of time since the previous maintenance. Examples of routine maintenance include scheduled oil changes, rotation of tires, brake checks, etc. This part of maintenance costs is similar to most vehicles in the same category. Additional maintenance costs, also referred to as CM cost, includes all expenditures for repair and rehabilitation. The maintenance cost was added up to get a fiscal year maintenance spending since there was not much information available about the routine maintenance cost from Oats, Inc.

To determine whether the OP method is able to predict the status of the Oats, Inc., fleet accurately, raw data was analyzed using the Statistical Analysis System (SAS). Maintenance costs were aggregated into a single category. As explained earlier, data for determining the passenger count for each vehicle and the mileage driven on unpaved roads could not be broken out for each vehicle. Therefore, these two parameters were not included in the predictor's vector. Hence, only vehicle age, mileage and total maintenance costs were considered as predictors.

After quantifying age, mileage and maintenance cost, the SAS was used to conduct further analysis.

Examining the Observed Data

Before making any judgments based on the raw data from Oats, Inc., the data set was examined to make sure there were no obvious logical errors. Having found none, it was analyzed using SAS. Descriptive statistics from SAS MEANS procedure, presented in Figure 2, give a concise summary for those observations. The output is presented in Figure 3.

SAS MEANs Proc

```
filename test 'OATS -raw.dat';

proc SORT data=Project;
  by CS;
run;
proc MEANS data=Project;
  var Age Mile MCost;
  by  CS;
run;
```

Figure 2. SAS MEANS procedure source codes

The SAS MEANS procedure briefly summarizes the raw data. The summary shows the data set contains 52 observations. Eleven original data points of January 2001 were taken out for verification purposes. Usually, the more miles a vehicle was driven, the worse condition it should be in. Contrary to expectations, the SAS MEANS summary shows that some vehicles with older age are still in good condition. For example, the maximum vehicle age in condition state 2 is 151 months but the maximum vehicle age in condition state 1 is only 103 months.

SAS MEANS Result

CS=1

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	6	74.3333333	16.5247289	55.0000000	103.0000000
MILE	6	157137.00	34425.02	111996.00	204062.00
MCOST	6	284.2116667	312.2105741	127.5000000	920.2800000

CS=2

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	14	68.5000000	46.0313438	19.0000000	151.0000000
MILE	14	124604.21	48030.58	36198.00	192485.00
MCOST	14	124.6042857	178.4064264	0	498.9400000

CS=3

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	13	20.8461538	7.5591683	10.0000000	36.0000000
MILE	13	70679.00	25313.29	42786.00	132925.00
MCOST	13	243.0661538	221.1792229	0	648.0000000

CS=4

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	19	5.7894737	5.6625372	0	17.0000000
MILE	19	17406.95	17737.37	0	49230.00
MCOST	19	47.9721053	119.4272702	0	524.9800000

Figure 3. Raw data points analyzed by SAS MEANS procedure

One explanation for this unusual phenomenon is that the vehicle may be sitting in the garage and was driven fewer miles as its age continued to grow. However, the mileage comparison broke this assumption. Mileage increases over time. Therefore, it must be an observation error to assign the vehicle’s condition state to 2, which it should be in condition state 1. In this case, five data points in condition state 2 that have higher ages and mileages than the maximum age and mileage in condition state 1 were removed from the raw data set. The remaining 47 observations, referred to as an adjusted data set, were analyzed by SAS and the results of the SAS MEANS procedure with no obvious error are presented in Figure 4.

SAS MEANS Results

```
-------------------------------- CS=1 ------------------------------
Variable   N          Mean       Std Dev       Minimum       Maximum
--------------------------------------------------------------------
AGE        6    74.3333333    16.5247289    55.0000000   103.0000000
MILE       6     157137.00      34425.02     111996.00     204062.00
MCOST      6   284.2116667   312.2105741   127.5000000   920.2800000
--------------------------------------------------------------------

--------------------------------- CS=2 -----------------------------
Variable   N          Mean       Std Dev       Minimum       Maximum
--------------------------------------------------------------------
AGE        9    42.1111111    20.9072024    19.0000000    91.0000000
MILE       9     101183.22      39265.47      36198.00     155841.00
MCOST      9   138.3911111   161.9537977             0   419.1500000
--------------------------------------------------------------------

------------------------------- CS=3 -------------------------------
Variable   N          Mean       Std Dev       Minimum       Maximum
--------------------------------------------------------------------
AGE       13    20.8461538     7.5591683    10.0000000    36.0000000
MILE      13      70679.00      25313.29      42786.00     132925.00
MCOST     13   243.0661538   221.1792229             0   648.0000000
--------------------------------------------------------------------

------------------------------- CS=4 -------------------------------
Variable   N          Mean       Std Dev       Minimum       Maximum
--------------------------------------------------------------------
AGE       19     5.7894737     5.6625372             0    17.0000000
MILE      19      17406.95      17737.37             0      49230.00
MCOST     19    47.9721053   119.4272702             0   524.9800000
--------------------------------------------------------------------
```

Figure 4. Adjusted data set analyzed by SAS MEANS procedure

SAS CORR Procedure Analysis

To determine the general trends between the predictors and condition states and to measure the strength of the relationship between the independent variables and the dependent variables, SAS CORR procedure was used. Let *r* represent the correlation coefficient, which ranges from –1.0 to +1.0. An *r* equal to +1.0 corresponds to a perfect positive trend and an *r* equal to –1.0 corresponds to a perfect negative trend. An *r* equal to 0 corresponds to no clear upward or downward trend. Figure 5 presents the analysis result by SAS CORR procedure. Each cell contains the correlation coefficient *r*-value and a p-value.

SAS CORR Results

Pearson Correlation Coefficients / Prob > |R|
under Ho: Rho=0/N = 47

	CS	AGE	MILE	MCOST
CS	1.00000	-0.88073	-0.87265	-0.34154
	0.0	0.0001	0.0001	0.0188
AGE	-0.88073	1.00000	0.90666	0.20646
	0.0001	0.0	0.0001	0.1638
MILE	-0.87265	0.90666	1.00000	0.41979
	0.0001	0.0001	0.0	0.0033
MCOST	-0.34154	0.20646	0.41979	1.00000
	0.0188	0.1638	0.0033	0.0

Figure 5. Adjusted Data Set Analyzed by SAS CORR procedure

The p-value is the significance probability for testing the null hypothesis that the true correlation between any pair variables is 0. It is the probability that the value of the test statistic could have occurred if the null hypothesis were true. From Figure 5, small p-values show the independent variables, such as age, mileage, and maintenance cost, have a strong relationship with the dependent variable – vehicle condition state. For example, *r* is –0.88 between age and condition state, which reflects a very clear downward trend between them. The p-value associated with it is 0.0001, which gives strong evidence that strong correlation exists between age and condition states.

An interesting phenomenon is the correlation between independent variables. From the SAS CORR procedure's analysis result, the correlation between age and mileage is 0.91, which reflects a very strong upward trend relationship. The p-value is 0.0001, which also supports that age and mileage are highly correlated and they are not independent. Therefore, only one of them is a good predictor. It is common that a vehicle has been driven a longer time usually has a higher mileage. However, the age may not be a good predictor since it is not a random variable. Therefore, it's possible that age has affection to the condition states due to mileage. To better see the contributions of other dependent variables to the independent variable, the partial and semi-partial correlations were introduced.

With a partial correlation, the variability in both the dependent and independent variables that is accounted for by another variable is removed prior to correlating the independent and dependent variables. Partial correlation examines the proportion of variance in the dependent variable that is not explained by the other independent variables but is uniquely accounted for by the only independent variable considered. The semi-partial correlation is the correlation of the individual predictor with the dependent variable after removing all the variability that predictor shares with other predictors. It examines the proportion of variance in the dependent variable that is uniquely accounted for by that independent variable.

In statistical analysis, the difference between a semi-partial correlation and a correlation is whether variation is removed from both the dependent variable and the independent variable. With a semi-partial correlation, only the variance in the independent variable that is shared with another variable is removed prior to correlating the independent variable with the dependent variable. The analysis of the significance of the parameter weights in a regression analysis is the test of whether the semi-partial correlations are significant.

In SAS, both partial and semi-partial correlations can be obtained by using procedure REG with options PCORR1and SCORR1. The code is listed in Figure 6 and the result is presented in Figure 7.

SAS Codes

```
proc REG data=Project;
   Model CS= Age Mile MCost / scorr1 pcorr1;
 run;
```

Figure 6. Source code of correlation analyzed by SAS REG procedure

From the SAS results shown in Figure 7, the analysis of variance result shows that the R-square, which is the fraction of the total variation in dependent variable due to the independent variables, is 81 percent. The combination of mileage, maximum passenger capacity and maintenance expenditure accounts for 81 percent of the total variance of the condition states. The squared semi-partial correlation of mileage is 76 percent, which means 76 percent of the variance in condition state is accounted for by mileage. That shows that mileage is a good predictor of condition state. Similarly, the semi-partial analysis of mileage also yielded the same results.

SAS Results

```
                         Analysis of Variance

                         Sum of        Mean
Source         DF        Squares       Square       F Value       Prob>F

Model          3         42.17401      14.05800     62.057        0.0001
Error          43         9.74088       0.22653
C Total        46        51.91489

Root MSE        0.47595       R-square       0.8124
Dep Mean        2.95745       Adj R-sq       0.7993
C.V.           16.09340

                          Parameter Estimates

                                                                   Squared       Squared
                     Parameter   Standard   T for H0:                     Semi-partial  Partial
Variable  DF      Estimate    Error      Parameter=0   Prob > |T|   Corr Type I   Corr Type I

INTERCEP   1      5.450786    0.42253378     12.900      0.0001          .             .
MILE       1   -0.000017883   0.00000143    -12.525      0.0001     0.76151508    0.76151508
MAXPC      1   -0.152532      0.04501216     -3.389      0.0015     0.05067143    0.21247226
MCOST      1    0.000076589   0.00037522      0.204      0.8392     0.00018180    0.00096799
```

Figure 7. Correlation analysis result by SAS REG procedure

What is also worth noticing is that the maintenance cost, which is the summation of the routine maintenance spending and other maintenance expenditures, does not explain the variance of the condition states. Usually, the more money spent on vehicle maintenance, the better condition state the vehicle should be in. Therefore, the summation of maintenance cost is not quite consistent with the analysis. Further OP analysis in the following section verified that.

MODEL TESTING

Using the 47 adjusted observations, the SAS PROBIT procedure was used to find the best combinations of those independent variables to predict condition states precisely. Sample SAS code is presented in Figure 8 and the results are shown in Figure 9.

SAS Code

```
proc sort;
   by Age Mile MaxPC MCost;
 run;

 proc probit data=Project;
  class CS;
  model CS = Age Mile MaxPC MCost / LACKFIT;
 run;
```

Figure 8. Sample SAS PROBIT procedure source codes

```
                          SAS PROBIT proc Results
                             Probit Procedure
Class Level Information
                      Class    Levels    Values
                      CS            4    1 2 3 4
Number of observations used = 47

                            Probit Procedure

Data Set           =WORK.PROJECT
Dependent Variable=CS

Weighted Frequency Counts for the Ordered Response Categories

                           Level     Count
                            1          6
                            2          9
                            3         13
                            4         19

Log Likelihood for NORMAL -24.45208044
                         Probit Procedure

Variable  DF   Estimate  Std Err ChiSquare  Pr>Chi Label/Value

INTERCPT   1 -9.5804074 2.348582  16.64012  0.0001 Intercept
AGE        1 0.05345282 0.032804  2.655143  0.1032
MILE       1 0.00002446 0.000015  2.611721  0.1061
MAXPC      1 0.28140284 0.181804  2.395785  0.1217
MCOST      1 0.00122238 0.001261  0.939766  0.3323
INTER.2    1 3.00537955 0.966032                         2
INTER.3    1 5.09951443 1.164313                         3
```

Figure 9. SAS PROBIT procedure analysis results

From the SAS results, the estimated β 's are shown in the estimate column. And μ 's are calculated as follows:

$$
\begin{aligned}
\mu_0 &= Intercept = -9.5804074 \\
\mu_1 &= Intercept + Intercept\ 2 = -9.5804074 + 3.00537955 = -6.57502785 \\
\mu_2 &= Intercept + Intercept\ 3 = -9.5804074 + 5.09951443 = -4.48089297
\end{aligned} \tag{4}
$$

The results are shown in Table 8.

Table 8. Coefficients estimated by SAS PROBIT procedure

Estimated Coefficients						
Age	**Mileage**	**MaxPC**	**Mcost**	**Threshold1**	**Threshold2**	**Threshold3**
β_1	β_2	β_3	β_4	μ_0	μ_1	μ_2
0.05345282	0.00002446	0.28140284	0.00122238	-9.5804074	-6.57502785	-4.48089297

This result shows four fitted regression lines as

$$\begin{aligned}
\Pr ob(CS=1) &= \Phi(-9.5804 + 0.5345 \times Age + 0.00002446 \times Mileage \\
&\qquad + 0.2814 \times MaxPC + 0.0012 \times MCost) \\
\Pr ob(CS=2) &= \Phi(-9.5804 + 3.0054 + 0.5345 \times Age + 0.00002446 \times Mileage \\
&\qquad + 0.2814 \times MaxPC + 0.0012 \times MCost) - \Pr ob(CS=1) \\
\Pr ob(CS=3) &= \Phi(-9.5804 + 5.0995 + 0.5345 \times Age + 0.00002446 \times Mileage \\
&\qquad + 0.2814 \times MaxPC + 0.0012 \times MCost) - \Pr ob(CS=2) \\
\Pr ob(CS=4) &= 1 - \Pr ob(CS=3)
\end{aligned} \tag{5}$$

The predicted probabilities of changing to each condition state in year 2001 are presented in Table 9. Age is measured in months and the probabilities are in percentage format. Data shown in Table 9 was not used to construct the PROBIT model; it was used to measure the accuracy of the prediction. By comparing the predicted most-likely condition states to the observed condition states in Table 9, the results were found to be inaccurate. For example, a vehicle 163 months old that has been driven for 198,210 miles with 0 dollars maintenance, was predicted to be in condition state 1 instead of the observed condition state 2.

Table 9. Predicted probabilities of selected vehicles

Age	Mileage	MaxPC	MCost	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Predicted CS	Observed CS	Accurate
163	198210	10	0	100.00	0.00	0.00	0.00	1	2	No
89	216531	6	0	68.46	31.52	0.02	0.00	1	1	No
60	138676	10	437.75	100.00	0.00	0.00	0.00	1	2	No
49	114020	10	0	0.00	12.41	70.21	17.38	3	2	No
51	144438	10	0	0.05	38.02	58.26	3.67	3	2	No
37	93234	8	259	100.00	0.00	0.00	0.00	1	3	No
34	100795	8	0	0.00	1.12	41.41	57.47	4	3	No
33	134408	8	353	100.00	0.00	0.00	0.00	1	3	No
25	71302	9	40	100.00	0.00	0.00	0.00	1	3	No
25	65739	9	0	0.00	0.01	6.34	93.64	4	3	No

Other combinations of the independent variables, such as age and mileage or only mileage and maintenance cost, yielded similar results. Therefore, the model and data set needs to be calibrated. Raw data was reviewed again and several problems were identified. For one thing, the survey did not collect much information about the routine maintenance expenditure. For example, vehicle number 496 was driven for five consecutive years from January 1993 to January 1997 with no routine maintenance expenditure. It's obvious that the routine maintenance cost was missing. For another, the observed vehicle condition state defined by FTA is too rough to follow. The observer could not clearly define the vehicle's condition state, especially in boundary situations. Hence, the adjusted data set contains 47 observations that need to be refined.

Data Refinement

From previous analysis, data collected from Oats, Inc., does not reflect the lifetime maintenance activities. Since the data inquiry form was designed to collect preventive maintenance expenditures and major repair activity expenditures, the maintenance cost should play a key role in the prediction according to formal analysis by others. Further study divided the maintenance cost into two parts, routine preventive maintenance expenditure and extra corrective activity expenditure. Since some routine maintenance cost information was missing, a reasonable estimation to those vehicles in category 2 of 720 dollars per year was adopted in this research. The description of vehicles in category 2 can be found in Appendix A.

As one will note, there were no data about vehicles in condition state 0. Data about mileage and maintenance cost when vehicles deteriorate to a condition state 0 are critical to predicting probabilities of transferring from other condition states to condition state 0. Meanwhile, it's critical for fleet managers to make budget allocations to replace old vehicles to improve service quality. Therefore, based on a vehicle's existing driving and maintenance activities, a group of data was added to the adjusted data set with 47 observations. Details are described as follows.

If a vehicle has reached condition state 2 or 1, several data points were extrapolated until it reached condition state 0. For example, a vehicle in condition 1 with 216,531 miles and 89 months old with no extra maintenance was assumed to deteriorate to condition state 0 by the time it was 101 months, 229,000 miles and received no extra maintenance expenditure. A data point with CS 0, age 101, mileage 229,000, same PM but zero CM cost was added to the adjusted data set. Similarly, to each old vehicle, one or more data points were added to illustrate its whole life cycle based on its average driving mileage in each year and current condition state.

Another consideration is that different agencies have different maintenance policies. Some agencies may provide a lot more money for routine maintenance than other agencies. With only minimum maintenance, vehicles should tend to deteriorate faster and more money is required to do corrective maintenance. One of our research goals was to understand vehicle deterioration process under different maintenance policies.

To compare the impact of different maintenance policies on a vehicle's condition rating, a group of data points with the same age and mileage as the existing data set, but with different maintenance costs and condition state were appended to the modified data set. The maintenance costs selected represented an annual cost of 720 dollars for doing four oil changes, changing tires and other components and routine inspection every year. A minimum maintenance routine cost of 60 dollars was assigned to vehicles that required only two oil changes annually.

For example, for a vehicle in condition state 2, which is 31 months old, 61,776 miles, and using 720 dollars as routine maintenance cost, another data point for the same condition state, age, and mileage, but with the routine maintenance cost of 60 dollars per year was appended to the data set. Under this extreme minimum maintenance condition, once a vehicle was in condition state 2, the agency has to spend significant resources on corrective maintenance to maintain the vehicle in service. After the corrective maintenance or overhaul, a vehicle would be able to perform normal service again and its useful life is extended.

For example, for a vehicle overhauled as shown in Table C3, which was in condition state 2, running for 43 months and 88,037 miles, 3,000 dollars was spent on overhaul and it was brought back to condition state 3. In addition, the appended data about the vehicles demonstrates that those with 60 dollars per year in preventive maintenance deteriorate faster than well-maintained vehicles. For instance, Table 10 shows the same vehicle, but the appended data illustrate that the vehicle only lasted for 67 months under 60 dollars poor maintenance policy while it can serve for 175 months under the 720 dollars maintenance policy.

Table 10. Data set illustration

Indication	CS	Age	Mileage	PM	CM
	4	7	8066	420	0
	2	19	36198	720	92.91
	2	31	61776	720	400.65
	2	43	88037	720	0
	1	55	111996	720	120
	1	67	131947	720	148.7
	1	79	147026	720	172.72
	2	91	151800	720	0
	1	103	159980	720	153.07
	2	115	166612	720	0
	2	127	172053	720	0
	2	139	187845	720	0
	2	151	192485	720	0
	2	163	198210	720	0
Added	0	175	204000	720	0
Appended	4	7	8066	35	0
Appended	3	19	36198	60	0
Appended	2	31	61776	60	0
Overhauled	3	43	88037	60	3000
Appended	2	55	100000	60	0
Appended	0	67	110000	60	0

Note: Age is measured in months, mileage is measured in miles, and PM and CM are in U.S. dollars.

To compare different maintenance plans, besides the 720 dollars of routine maintenance, other amounts shown in Table 11 were introduced to compare different maintenance policies while the 60 dollars routine maintenance were left unchanged as base line. Theoretically, as the preventive maintenance cost varies, the condition state changes. However, since the definition of condition states by FTA is vague and the difference between any two adjacent condition states are undetermined, there is a safe range where preventive maintenance cost varies while the condition state stay unchanged. In reality, slightly increasing or decreasing the preventive maintenance will not alternate the condition state. In addition, the OP model is proposed because the boundary of the range is uncertain.

Table 11. Preventive maintenance cost used

Preventive Maintenance Cost	Ratio Compared with $720
$1,500	2.1
$1,400	1.9
$1,300	1.8
$1,200	1.7
$1,100	1.5
$1,080	1.5
$900	1.3
$800	1.1
$720	1.0
$480	1.5
$360	2.0
$240	3.0
$180	4.0
$144	5.0
$120	6.0
$103	7.0
$90	8.0
$80	9.0
$72	10.0

In conclusion, there are 19 different data sets. Each data set contains two parts of data as illustrated in Figure 10. Both parts hold identical vehicle age and mileage information, but have different maintenance spending. Part one, which is the original observation data, holds the maintenance policy of spending more than 60 dollars per year in preventive maintenance to avoid high corrective maintenance cost. Part two holds the 60 dollars per year minimum routine maintenance cost with 3,000 dollars in corrective maintenance costs when the vehicle is overhauled.

Part I: Observed Data PM. Varies
Part II: Minimum maintenance Data PM = $60

Figure 10. Data set structure illustration

The difference among those data sets is that the preventive routine maintenance in part one is different, which varies from 1,500 to 72 dollars as shown in Table 11. The variation range of the preventive maintenance may be a little large and the analysis result may be biased. However, it is useful to view the overall trend of marginal effects as illustrated in the next section.

The assumptions above were based on common sense and estimation based on the limited available data. Further study is to demonstrate the methodology instead of reaching a solid conclusion from the data sets. This approach was taken to overcome the fact that sufficient data could not be collected from the service agencies. If the analysis works, then it will provide a framework for further analysis when more data becomes available.

Refined Data Analysis

After the original data set was refined, the SAS MEANS, CORR and REG procedures were used again to test those data sets. The summary statistic analysis by MEANS was presented in Figure 11, the correlation analysis by CORR procedure is presented in Figure 12 and the REG procedure analysis is presented in Figure 13.

In the MEANS procedure result, well-maintained vehicles with higher mileage and age were still in condition state 2, even better than poorly maintained vehicles in condition state 1 with less age and mileage. For example, the maximum age of vehicles in condition state 2 was 163 months, but the maximum age of vehicles in condition state 1 was only 103 months.

From the SAS CORR results, the r-value of age and condition state is –0.626, which demonstrates a relatively strong negative relationship. Nevertheless, the relationship between mileage and condition state is even stronger, with a –0.706. It reflects the fact that when mileage goes higher, the condition states get worse in this data set. Compared with mileage, the correlations between routine maintenance cost (PM), extra maintenance cost (CM) and vehicles' condition states were relatively weak since the numbers were very close to 0.

The SAS CORR analysis also shows that vehicle age and mileage have a high positive correlation, with a correlation coefficient of 0.885. The correlations among mileage and maintenance costs are relatively weak, only 0.52 and 0.24, respectively.

SAS MEANS Results

CS=0

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	8	71.1250000	46.1563724	41.0000000	175.0000000
MILE	8	124879.63	58029.73	75000.00	229000.00
PM	8	225.0000000	305.5206329	60.0000000	720.0000000
CM	8	0	0	0	0

CS=1

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	14	56.8571429	23.7773556	25.0000000	103.0000000
MILE	14	126528.79	49702.30	65000.00	216531.00
PM	14	390.0000000	342.4571843	60.0000000	720.0000000
CM	14	107.5714286	194.4240861	0	728.0000000

CS=2

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	28	55.2857143	43.2108158	13.0000000	163.0000000
MILE	28	108372.64	48126.38	36198.00	198210.00
PM	28	484.2857143	322.0470241	60.0000000	720.0000000
CM	28	46.0000000	126.0191050	0	438.0000000

CS=3

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	26	21.2692308	7.9977882	10.0000000	37.0000000
MILE	26	64971.92	29433.13	15936.00	134408.00
PM	26	512.3076923	308.3933552	60.0000000	720.0000000
CM	26	59.6923077	122.8855628	0	485.0000000

CS=4

Variable	N	Mean	Std Dev	Minimum	Maximum
AGE	27	5.4444444	5.1165894	0	17.0000000
MILE	27	15823.44	15696.88	450.0000000	49230.00
PM	27	231.4814815	286.5404214	0	720.0000000
CM	27	23.9259259	99.7993857	0	515.0000000

Figure 11. Refined data sets analysis result by SAS MEANS procedure

SAS CORR Results

Correlation Analysis

5 'VAR' Variables: CS AGE MILE PM CM

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
CS	103	2.485437	1.235616	256.000000	0	4.000000
AGE	103	35.077670	35.986569	3613.000000	0	175.000000
MILE	103	76907	56995	7921377	450.00000	229000
PM	103	392.135922	328.757764	40390	0	720.000000
CM	103	48.466019	126.958293	4992.000000	0	728.000000

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 /N=103

	CS	AGE	MILE	PM	CM
CS	1.00000	-0.62637	-0.70596	-0.06871	-0.06783
	0.0	0.0001	0.0001	0.4904	0.4960
AGE	-0.62637	1.00000	0.88515	0.42969	0.06915
	0.0001	0.0	0.0001	0.0001	0.4877
MILE	-0.70596	0.88515	1.00000	0.54276	0.24181
	0.0001	0.0001	0.0	0.0001	0.0139
PM	-0.06871	0.42969	0.54276	1.00000	0.38006
	0.4904	0.0001	0.0001	0.0	0.0001
CM	-0.06783	0.06915	0.24181	0.38006	1.00000
	0.4960	0.4877	0.0139	0.0001	0.0

Figure 12. Refined data sets analysis result by SAS CORR procedure

SAS REG proc Results

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	3	99.45350	33.15117	58.320	0.0001
Error	99	56.27466	0.56843		
C Total	102	155.72816			

Root MSE	0.75394	R-square	0.6386
Dep Mean	2.48544	Adj R-sq	0.6277
C.V.	30.33445		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|	Squared Semi-partial Corr Type I	Squared Partial Corr Type I
INTERCEP	1	3.407638	0.13196550	25.822	0.0001	.	.
MILE	1	-0.00002054	0.00000156	-13.157	0.0001	0.49837997	0.49837997

Figure 13. Refined data sets analysis results by SAS REG procedure

The semi-partial correlation coefficient in Figure 13 shows that almost 50 percent of a vehicle's condition state variance is accounted for by the variance of mileage and 14 percent of it is accounted for by the variance of routine preventive maintenance expenditure. That explains the importance of mileage and routine preventive maintenance as predictors.

The analysis by SAS PROBIT procedure is revealed in Figure 14. The p-value for each predicted coefficients is presented under the "Pr>chi" column. The coefficient for mileage and preventive routine maintenance costs are significant since their p-value is very small, only 0.0001. Contrarily, the coefficients of age and extra maintenance cost are less significant. Thus, if age and corrective maintenance costs were removed, the predicted probabilities would not vary much. The SAS PROBIT procedure analysis for independent variables of mileage and preventive maintenance is presented in Figure 15. The log-likelihood was used to compare the relative accuracy of the model. Since the PROBIT procedure uses the maximum likelihood method to estimate β's and μ's, the larger the likelihood, the better the result.

```
                             Probit Procedure

                          Class Level Information
                         Class    Levels    Values
                       CS            5    0 1 2 3 4

                     Number of observations used = 103
                             Probit Procedure
                   Data Set          =WORK.PROJECT
                   Dependent Variable=CS
Weighted Frequency Counts for the Ordered Response Categories
                       Level     Count
                         0         8
                         1        14
                         2        28
                         3        26
                         4        27

Log Likelihood for NORMAL -106.6975648

Variable  DF   Estimate  Std Err ChiSquare  Pr>Chi Label/Value

INTERCPT   1 -3.9351152 0.405104  94.35845  0.0001 Intercept
AGE        1 -0.0064641 0.007062  0.837788  0.3600
MILE       1 0.00003374 5.506E-6    37.549  0.0001
PM         1  -0.002383  0.00048  24.63578  0.0001
CM         1 -0.0002913 0.000987  0.087074  0.7679
INTER.2    1 0.98330178 0.234323                             1
INTER.3    1  2.4987213 0.324186                             2
INTER.4    1 3.78337189 0.381141                             3
```

Figure 14. Refined data sets analysis results by SAS PROBIT procedure

SAS PROBIT proc Analysis

```
                    Probit Procedure
                 Class Level Information

               Class    Levels    Values

              CS            5    0 1 2 3 4

            Number of observations used = 103

                    Probit Procedure

Data Set          =WORK.PROJECT
Dependent Variable=CS

Weighted Frequency Counts for the Ordered Response Categories

                           Level     Count
                           0          8
                           1         14
                           2         28
                           3         26
                           4         27

Log Likelihood for NORMAL -107.1142911

Variable  DF   Estimate  Std Err ChiSquare  Pr>Chi Label/Value

INTERCPT   1 -3.8801175 0.400571  93.82768  0.0001 Intercept
MILE       1 0.00002986 3.472E-6  73.97829  0.0001
PM         1 -0.0023704 0.000462  26.32875  0.0001
INTER.2    1 0.97785151 0.232843                             1
INTER.3    1 2.51180164 0.325823                             2
INTER.4    1 3.77972664 0.380863                             3
```

Figure 15. Refined data set analysis by SAS PROBIT procedure with fewer predictors

With age and additional maintenance expenditure included as predictors, the log likelihood is –106.6976. Without them, the log likelihood is –107.1143. The difference is only 0.4167, which is not significant. Since the data is limited, the impact of age and corrective maintenance cost may not be fully understood. Therefore, age and mileage were still included as predictors since the log likelihood is still slightly higher than excluding them as predictors. The predicted probabilities for selected data, which were not included in the model building but were used to check the accuracy, are shown in Tables 12 and 13.

Table 12. Predicted probabilities of using age, mileage, PM, and CM as predictors

Age	Mileage	PM	CM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Observed CS	Predicted CS	Accurate
163	198210	720	0	49.33	33.98	16.04	0.65	0.01	2	0	No
89	216531	720	0	85.98	12.06	1.94	0.02	0	1	0	No
60	138676	720	438	6.85	23.87	53.7	14.51	1.08	2	2	Yes
49	114020	720	0	1.7	11.07	51.96	30.45	4.82	2	2	Yes
51	144438	720	0	13.41	31.66	46.73	7.83	0.37	2	2	Yes
37	93234	720	259	0.24	3.07	34.09	45.83	16.76	3	3	Yes
34	100795	720	0	0.68	6.18	44.3	39.4	9.45	3	2	Yes
33	134408	720	353	7.61	25.07	53.1	13.37	0.94	3	2	No
25	71302	720	40	0.03	0.71	17.14	46.36	35.76	3	3	Yes
25	65739	720	0	0.02	0.43	13.21	43.83	42.51	3	3	Yes

The predicted vehicle condition state is the highest probability of the five forecasted probabilities of being in each condition state. For example, in Table 12, to a vehicle with observed condition state 2, 163 months old, has been driven 198,210 miles, with 720 dollars spent on routine maintenance, the forecasted condition state is 0 instead of 2 with 49.33 percent probability. Since the probability difference between being in condition state 0 and 2 is big, one can see the prediction is not accurate.

Table 13. Predicted probabilities of using mileage and PM as predictors

Age	Mileage	PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Observed CS	Predicted CS	Accurate
163	198210	720	63.00	27.49	9.29	0.22	0.00	2	0	No
89	216531	720	81.02	15.81	3.13	0.03	0.00	1	0	Yes
60	138676	720	7.41	24.58	53.69	13.34	0.98	2	2	Yes
49	114020	720	1.45	9.97	51.49	31.58	5.51	2	2	Yes
51	144438	720	10.14	28.22	50.85	10.18	0.61	2	2	Yes
37	93234	720	0.25	3.15	35.15	45.02	16.43	3	3	Yes
34	100795	720	0.50	4.99	41.91	41.15	11.46	3	2	Yes
33	134408	720	5.78	21.79	55.02	16.03	1.37	3	2	No
25	71302	720	0.03	0.63	16.55	45.42	37.37	3	3	Yes
25	65739	720	0.01	0.39	12.90	42.89	43.81	3	4	Yes

If the predicted condition state is the same as or very close to the observed condition, one can tell the prediction is accurate. For example, in Table 13, to a vehicle has been driven for 34 months and 100,795 miles, with 720 dollars spent annually on PM, the predicted probability of being in condition state 2 is 41.91 percent, and the predicted probability of being in condition state 3 is 41.15 percent. The difference is only 0.76 percent, which is insignificant. Under this condition, even the predicted most likely condition state is 2, and the observed condition state is 3, one can still say the prediction is relatively accurate. Based on this judgment, the accuracy of the prediction by suing different predictors is presented in Table 14.

Table 14. Comparison of prediction accuracies

Data Set	Raw Oats Data	Adjusted Oats Data	Adjusted Oats Data
Predictors	Age, Mileage, MaxPC, Mcost	Age, mileage, PM, CM	Mileage, PM
Accuracy (%)	0	80	80

After adjustment of the raw data, the accuracy of the prediction increased from 0 to 60 percent. Based on the analysis above of the log likelihood and p-value about the predictors, removing the age and extra maintenance cost from the predictor group slightly decreases log-likelihood value, therefore decreasing the prediction accuracy, based on the refined data set analysis results presented in Table 12 and 13, respectively. The prediction difference is illustrated in Table 15.

Table 15. Predicted probability comparison of different predictor sets

Observed CS	Age	Mileage	PM	CM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4
W/ 2	163	198210	720	0	49.33	33.98	16.04	0.65	0.01
W/O 2	163	198210	720	0	63.00	27.49	9.29	0.22	0.00
W/ 3	34	100795	720	0	0.68	6.18	44.30	39.40	9.45
W/O 3	34	100795	720	0	0.50	4.99	41.91	41.15	11.46
W/ 3	33	134408	720	353	7.61	25.07	53.10	13.37	0.94
W/O 3	33	134408	720	353	5.78	21.79	55.02	16.03	1.37

Note: W/ means predictors include age and PM cost, and w/o means predictors do not include age and CM cost.

From Table 15, a vehicle of 163 months that was driven 198,210 miles tends to be more likely in condition state 1 instead of the observed condition state 2. Hence, there were observation errors enrolled in the model. It also reflects that the definition of vehicle condition states by FTA is a little vague, especially in boundary conditions.

Since the condition states are discrete, it was hard to assign a vehicle's condition state while the vehicle was in a boundary situation. For example, to a vehicle observed in condition state 3, which was driven for 34 months and 100,795 miles, the predicted probability that the vehicle is in condition 3 is 41.15 percent while that in condition state 2 is 41.91 percent. The difference of probability being in either condition state is only 0.76 percent. Therefore, to increase the accuracy of the prediction, a more detailed condition state definition is necessary.

From the analysis above, the refined data sets displays a dramatic increase of accuracy. Meanwhile, it also verified that only mileage and preventive maintenance costs are key predictors and the OP model is qualified for this study. To better understand the impact of key predictors to vehicles deterioration process, a sensitivity analysis was conducted.

Sensitivity Analysis

The objective of the sensitivity analysis was to observe the impact of unit change of predictors on condition states. The goal of this sensitivity analysis was to determine the impact of changing the proposed maintenance plan on the fleet. Using the results found in previous chapters, it is desirable to consider the impact of preventive maintenance expenditure on condition states. To measure its impact on predicted vehicle condition states and demonstrate its application to a transit fleet, a study was conducted in several stages. In the first stage, SAS was used to estimate coefficients β and μ, subjected to an assumed value of annual preventive maintenance for each vehicle. Once those β and μ values were calculated for each case, PM value was allowed to vary over a wide range to observe its affect on predicted probabilities of condition states. The goal of this study stage is to observe vehicle deterioration process while keeping an existing maintenance plan.

The second stage is to address the question, “Is it better to spend operating dollars this year on vehicle maintenance, or can I wait and spend it later?” This study was conducted for a data set where the baseline preventive maintenance was set for a fleet at 720 dollars annually. Parameters β and μ were held constant. To the baseline condition, the fleet was allowed to age over a 3-year period. While the age and mileage were allowed to vary, the probabilities for each condition state for each vehicle were calculated. Then, PM values were set at 360 and 72 dollars annually per vehicle for the fleet. Next, CM was increased until the condition of the fleet was identical to the condition of the fleet with the baseline preventive maintenance value of 720 dollars. That study is to evaluates the impact of alternative maintenance strategies.

The third stage is similar to the first study with a significant difference. While in the first study the preventive maintenance was held constant, β and μ values in this stage from OP method were recalculated for each assumed value of preventive maintenance. The value of annual preventive maintenance varied from 72 to 1500 dollars per vehicle. This approach resulted in 19 data sets being considered. The impact of these assumptions was evaluated.

In each study, it was difficult to evaluate the impact of variables to the overall performance of vehicles because the OP method only gives probabilities for vehicles being in a given condition states. Thus, it became very difficult to evaluate vehicle overall performance under different maintenance strategies.

To help overcome this barrier, the concept of a weighted probability was introduced. In each of these studies, the weighted probability is defined as follows:

$$\begin{aligned} Weighted\mathrm{Pr}ob = {} & 5\times \mathrm{Pr}ob(CS=4)+4\times \mathrm{Pr}ob(CS=3)+3\times \mathrm{Pr}ob(CS=2)+2\times \mathrm{Pr}ob(CS=1) \\ & +1\times \mathrm{Pr}ob(CS=0) \qquad (5-1) \end{aligned}$$

This approach allows one to calculate the probabilities of each vehicle in each condition state and then compare the overall condition state of each vehicle.

Comparison of Weighted Probabilities

The goal of this study stage is to observe vehicle performance under existing maintenance budget as PM varies. In this analysis, β and μ's from SAS OP model were based on a known value of preventive maintenance. They were included in a spreadsheet to compute the predicted probabilities of for each condition state for the entire fleet. Then PM cost was increased from 72 to 1500 dollars, as shown in Table 11, to observe its impact on predicted probabilities. The weighted probability was defined to view the overall condition trend of the fleet.

To better illustrate the analytical procedures, a data set using 480 dollars as annual PM was used. As previously discussed, this data set represents two types of maintenance activities. One maintenance approach set the annual preventive maintenance costs at 480 dollars while the "minimal maintenance" set the annual preventive maintenance at 72 dollars. It was entered into SAS OP procedure and the estimated coefficients are presented in Table 16. When the preventive maintenance costs is set at 720 dollars per year per vehicle, the SAS OP estimated coefficients are presented in Table 17.

Table 16. SAS OP procedure estimated coefficients when PM is $480/year

Estimated Coefficients							
Age	**Mileage**	**PM**	**CM**	**Threshold 1**	**Threshold 2**	**Threshold 3**	**Threshold 4**
β_1	β_2	β_3	β_4	μ_0	μ_1	μ_2	μ_3
-0.004527	0.0000367	-0.0040302	-0.0003478	-4.6598992	-3.2721717	-1.51571	-0.1569655

Table 17. SAS OP procedure estimated coefficients when PM is $720/year

Estimated Coefficients							
Age	**Mileage**	**PM**	**CM**	**Threshold 1**	**Threshold 2**	**Threshold 3**	**Threshold 4**
β_1	β_2	β_3	β_4	μ_0	μ_1	μ_2	μ_3
-0.0045173	0.0000369	-0.0026507	-0.0003593	-4.7508081	-3.3528514	-1.5773341	-0.1998115

Once the estimated coefficients were determined, it was easy to predict the probabilities assuming PM values were changed for the upcoming year. To do this, two different vehicles were selected to illustrate the impact of changing PM values while the OP estimated coefficients stayed the same. Those two vehicles selected were in CS 2 and 3, respectively. The other parameters for the vehicle are present in Table 18.

Table 18. Two selected vehicles for illustration

Vehicle ID	CS	Age	Mileage	PM	CM
1	2	43	88,037	Varies	0
2	3	21	44,000	Varies	0

The preventive maintenance values were allowed to vary between 72 and 1500 dollars annually. For each preventive maintenance condition, the probabilities of the condition states for the next year were calculated. These values are presented in Tables 19 and 20 for the two vehicles.

Table 19. Predicted probabilities for vehicle 1 when PM = $480/year

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	2.77	27.11	59.16	10.48	0.48	278.79
80	2.57	26.20	59.65	11.05	0.53	280.76
90	2.34	25.07	60.20	11.79	0.60	283.22
103	2.07	23.63	60.82	12.80	0.69	286.41
120	1.75	21.79	61.43	14.20	0.83	290.58
144	1.37	19.30	61.93	16.32	1.08	296.44
180	0.94	15.84	61.85	19.81	1.57	305.23
240	0.48	10.94	59.53	26.26	2.80	319.98
360	0.10	4.46	48.14	39.61	7.68	350.30
480	0.02	1.47	32.39	48.84	17.28	381.89
600	0.00	0.39	18.03	49.28	32.30	413.47
720	0.00	0.08	8.25	40.70	50.96	442.54
800	0.00	0.03	4.38	32.04	63.55	459.12
900	0.00	0.01	1.74	20.92	77.33	475.57
1080	0.00	0.00	0.23	6.78	92.99	492.76
1100	0.00	0.00	0.18	5.81	94.01	493.83
1200	0.00	0.00	0.05	2.46	97.49	497.45
1300	0.00	0.00	0.01	0.90	99.09	499.08
1400	0.00	0.00	0.00	0.28	99.72	499.71
1500	0.00	0.00	0.00	0.08	99.92	499.92

Table 20. Predicted probabilities for vehicle 2 when PM = $480/year

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	0.03	2.09	37.13	46.87	13.87	372.46
80	0.03	1.94	36.06	47.38	14.60	374.58
90	0.02	1.76	34.72	47.96	15.54	377.24
103	0.02	1.54	32.99	48.63	16.82	380.69
120	0.02	1.30	30.75	49.34	18.60	385.22
144	0.01	1.01	27.66	50.02	21.30	391.60
180	0.01	0.68	23.26	50.29	25.76	401.11
240	0.00	0.34	16.77	48.76	34.13	416.67
360	0.00	0.07	7.52	39.44	52.97	445.31
480	0.00	0.01	2.75	26.07	71.16	468.39
720	0.00	0.00	0.20	6.16	93.94	493.45
800	0.00	0.00	0.07	3.16	96.77	496.70
900	0.00	0.00	0.02	1.20	98.78	498.77
1080	0.00	0.00	0.00	0.15	98.85	499.85
1100	0.00	0.00	0.00	0.11	98.89	499.89
1200	0.00	0.00	0.00	0.03	99.97	499.97
1300	0.00	0.00	0.00	0.01	99.99	499.99
1400	0.00	0.00	0.00	0.00	100.00	500.00
1500	0.00	0.00	0.00	0.00	100.00	500.00

To illustrate the trend in predicted condition states, predicted probabilities were plotted in Figure 16 for Vehicle 1 and Figure 17 for Vehicle 2. From both figures, the probability of a vehicle being in condition state 4, the best condition, increases as PM expenditure increases. Generally, the more resources spent on preventive maintenance, the better condition the vehicle will be in. Since the summation of the probabilities in each row in Table 19 and Table 20 has to be 100 percent, as the vehicle has higher probability of staying in condition state 4, the probabilities of transforming to other condition states decreases. In order to view the overall trend combined predicted probabilities in each condition state, the concept of weighted probability was applied. For example, in Table 19, when PM cost is 72 dollars, the weighed probability is

$$Weighted\ \Pr ob = 5\times 0.48 + 4\times 10.84 + 3\times 59.16 + 2\times 27.11 + 1\times 2.77 \approx 279 \qquad (6)$$

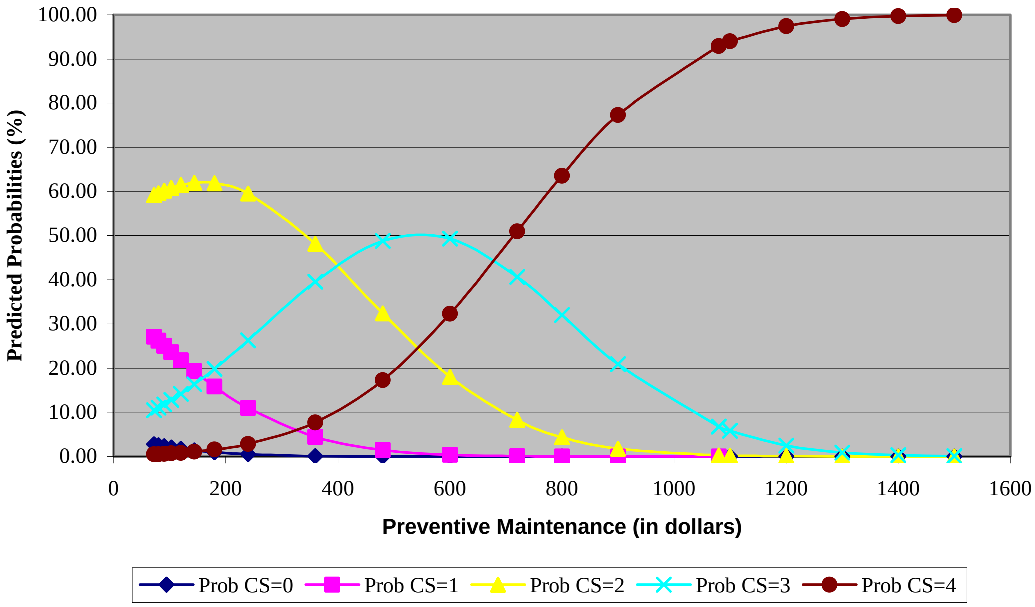

Figure 16. Predicted probabilities for vehicle 1 when PM = $480/year

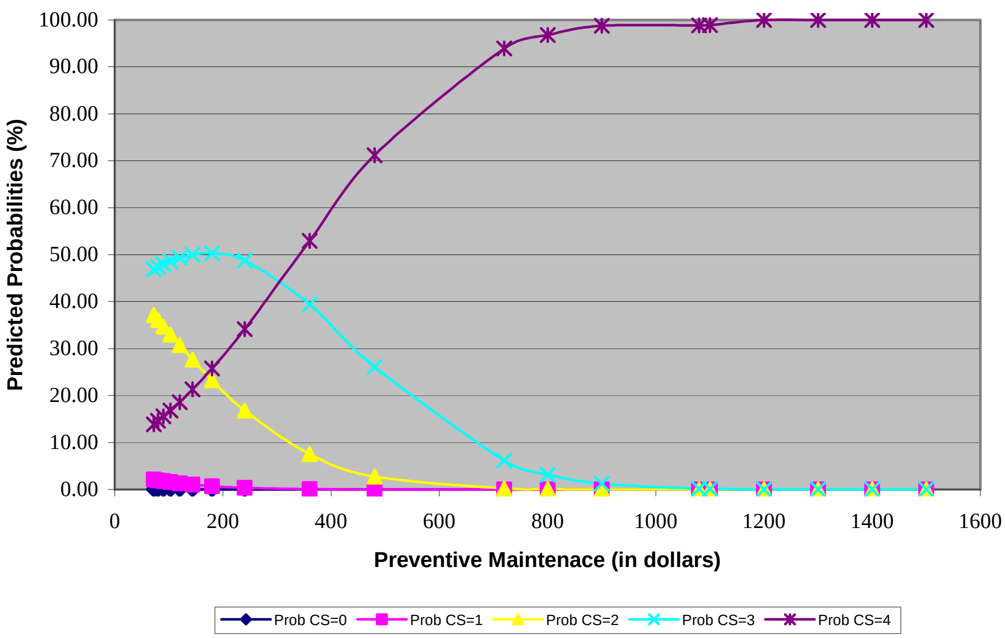

Figure 17. Predicted probabilities for vehicle 2 when PM = $480/year

The weighted probabilities shown in Tables 19 and 20 were plotted in Figures 18 and 19, respectively. It reflects the fact that the weighted probability increases as the preventive maintenance increases and the vehicle condition ratings become higher.

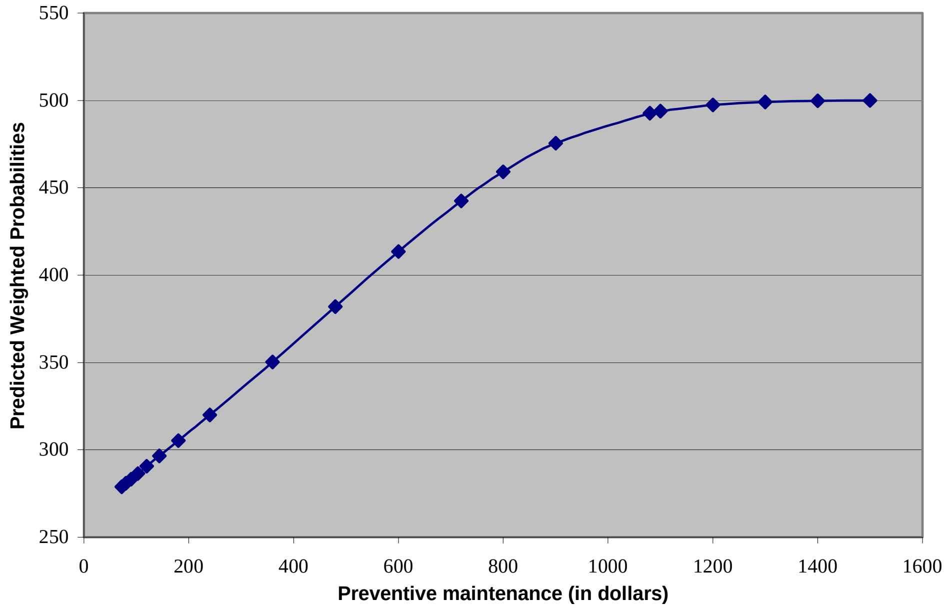

Figure 18. Weighted probabilities for vehicle 1 when PM = $480/year

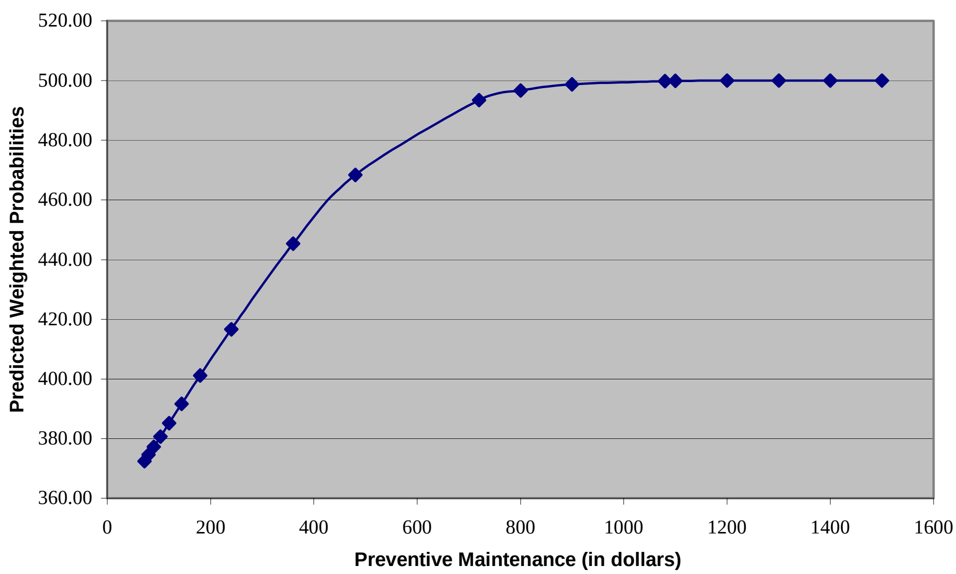

Figure 19. Weighted probabilities for vehicle 2 when PM = $480/year

To verify the results, another analysis using 720 dollars as PM was conducted. For the same vehicles, another data set using 720 dollars as annual PM was inputted into SAS OP model and the estimated parameters listed in Table 17 above. Predicted probabilities for vehicles in Table 18 are presented in Tables 21 and 22 respectively and plotted in Figures 20 and 21, respectively. The weighted probability charts are shown in Figures 22 and 23.

Table 21. Predicted probabilities for vehicle 1 when PM = $720/year

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	2.96	28.27	58.85	9.53	0.39	276.12
80	2.82	27.67	59.22	9.88	0.41	277.41
90	2.65	26.91	59.66	10.33	0.44	279.01
103	2.44	25.94	60.19	10.94	0.49	281.10
120	2.20	24.68	60.80	11.76	0.56	283.81
144	1.88	22.93	61.51	13.00	0.67	287.64
180	1.49	20.41	62.23	15.00	0.87	293.36
240	0.98	16.51	62.48	18.70	1.33	302.87
360	0.40	10.11	59.43	27.19	2.87	322.01
480	0.15	5.66	52.30	36.21	5.68	341.61
720	0.02	1.35	31.94	49.49	17.21	382.52
800	0.01	0.77	25.21	50.86	23.15	396.37
900	0.00	0.36	17.81	49.87	31.96	413.42
1080	0.00	0.08	8.21	41.38	50.33	441.96
1100	0.00	0.07	7.45	40.05	52.44	444.87
1200	0.00	0.03	4.40	32.79	62.79	458.35
1300	0.00	0.01	2.44	25.26	72.29	469.83
1400	0.00	0.00	1.27	18.31	80.41	479.14
1500	0.00	0.00	0.62	12.48	86.90	486.27

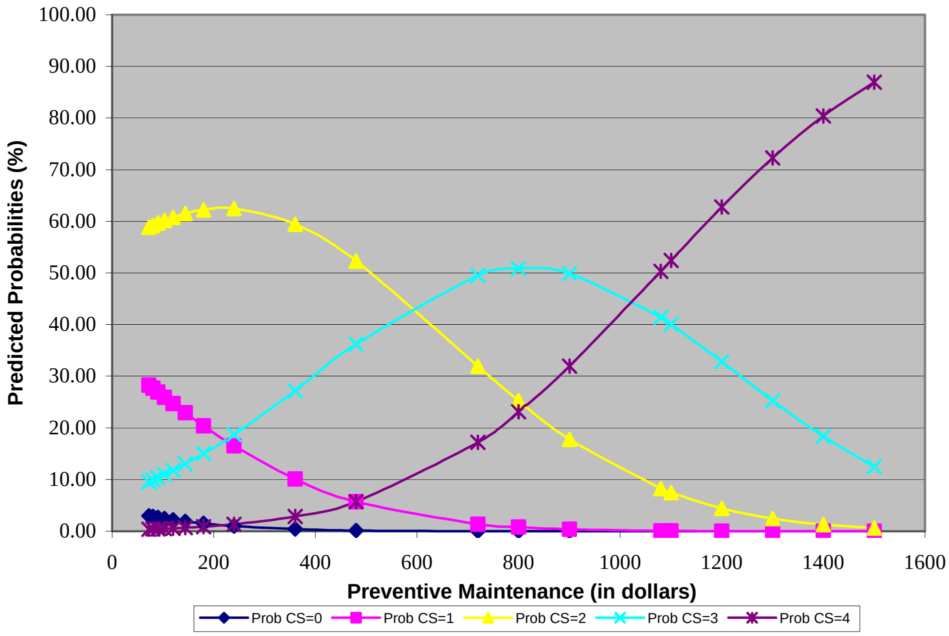

Figure 20. Predicted probability chart of vehicle 1 when PM = $720/year

Table 22. Predicted probabilities for vehicle 2 when PM=$720/year

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	0.03	2.24	38.82	46.45	12.46	369.06
80	0.03	2.13	38.11	46.83	12.90	370.44
90	0.03	2.00	37.22	47.29	13.47	372.17
108	0.02	1.84	36.07	47.84	14.23	374.41
120	0.02	1.65	34.56	48.51	15.27	377.35
144	0.02	1.40	32.45	49.32	16.82	381.51
180	0.01	1.10	29.34	50.23	19.32	387.75
240	0.01	0.72	24.40	50.90	23.98	398.12
360	0.00	0.28	15.86	48.99	34.87	418.44
480	0.00	0.10	9.46	43.26	47.18	437.51
720	0.00	0.01	2.59	25.99	71.41	468.80
800	0.00	0.00	1.55	20.29	78.15	476.59
900	0.00	0.00	0.77	14.08	85.14	484.36
1080	0.00	0.00	0.19	6.24	93.57	493.38
1100	0.00	0.00	0.16	5.63	94.21	494.05
1200	0.00	0.00	0.07	3.24	96.69	496.63
1300	0.00	0.00	0.03	1.75	98.23	498.20
1400	0.00	0.00	0.01	0.89	99.11	499.10
1500	0.00	0.00	0.00	0.42	99.58	499.57

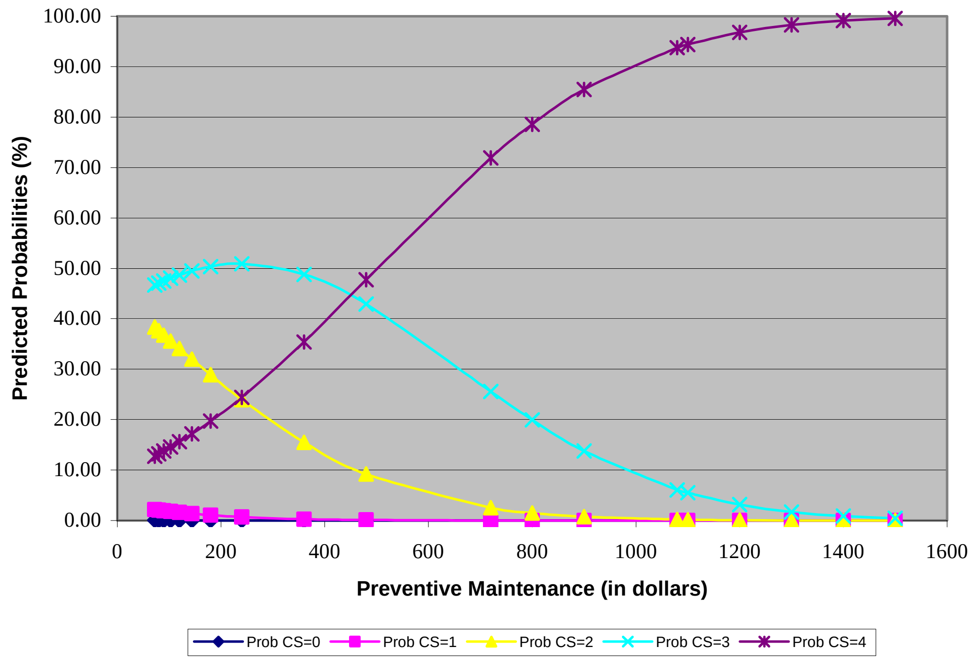

Figure 21. Predicted probability chart of vehicle 2 when PM = $720/year

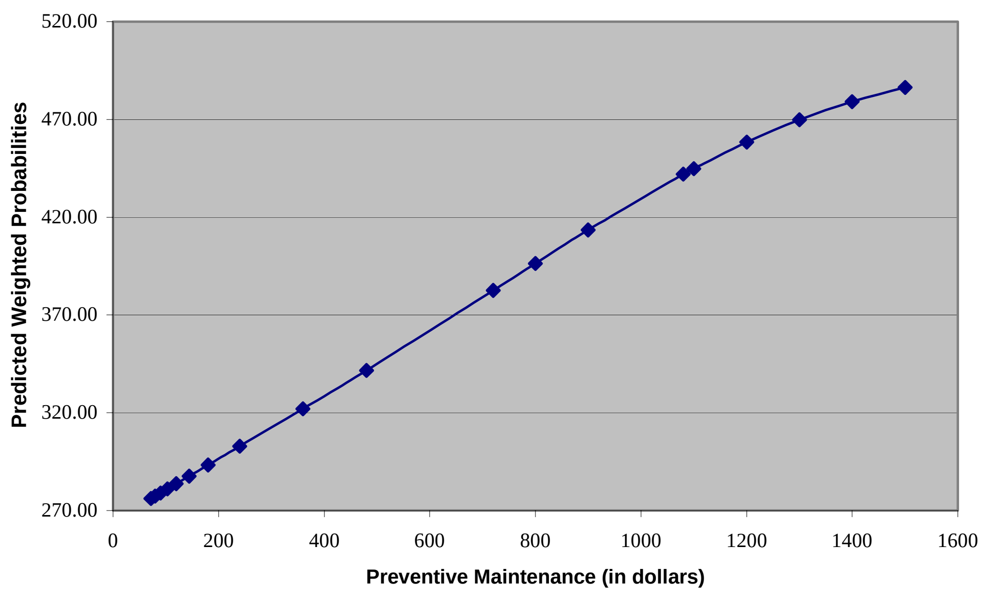

Figure 22. Weighted probabilities for vehicle 1 when PM = $720/year

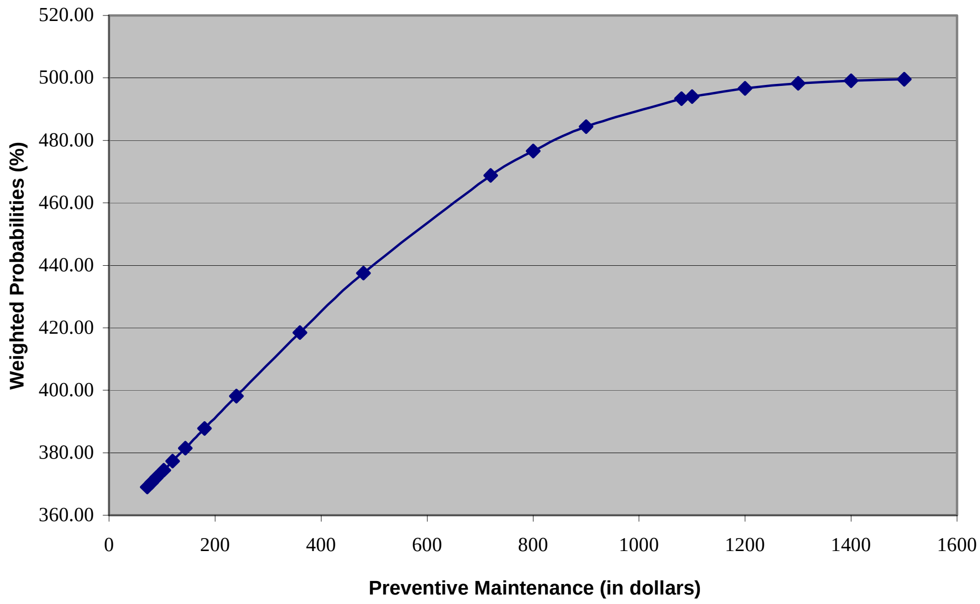

Figure 23. Weighted probabilities for vehicle 2 when PM=$720/year

From those figures and tables, one can see as preventive maintenance increases, the vehicle conditions become higher. The weighted probabilities move in the same direction as preventive maintenance cost. The weighted probability curve first goes up then tends to be flat as the preventive maintenance spending increases. It also illustrates that preventive maintenance is a critical predictor that has impact on the changing of condition states.

Comparison Of Alternative Maintenance Strategies

It is tempting to think of vehicle maintenance costs as an expense rather than an investment into the quality of the vehicle fleet. From the previous study, we have seen that vehicles are in better condition when preventive maintenance increases. In order to bring a fleet up to a higher condition based on present maintenance strategy, a certain amount of the budget has to be allocated to do corrective maintenance after a period of time. For example, if a vehicle is running under a policy of spending 360 dollars per year for preventive maintenance, it is valuable to know how much more should be spent on corrective maintenance next year to make the vehicle have the same probabilities as spending 720 dollars for preventive maintenance in the same period.

The following study looks at three different maintenance strategies using 72, 360, and 720 dollars, respectively, as preventive maintenance and calculates additional expenditure to bring the fleet up from using 72 or 360 dollars doing PM to the same conditions as spending 720 dollars for PM. This analysis was done on a fleet of 12 vehicles and their current conditions are outlined in Table 23. The average running mileage per year in the last column of Table 23 was calculated from the historical data presented. PM is 720 dollars per year; no CM was assumed.

Table 23. Selected vehicles

Vehicle	CS	Age	Mileage	PM	CM	Average Mileage/Year
1	2	163	198,210	720	0	14,626
2	1	89	216,531	720	0	29,165
3	2	60	138,676	720	0	27,645
4	2	49	114,020	720	0	25,880
5	2	51	144,438	720	0	33,622
6	3	37	93,234	720	0	28,655
7	3	34	100,795	720	0	36,896
8	3	33	134,408	720	0	43,469
9	3	25	71,302	720	0	32,982
10	3	25	65,739	720	0	30,530
11	3	22	132,925	720	0	70,321
12	3	14	63,446	720	0	57,348

The baseline preventive maintenance strategy was to spend 720 dollars per year per vehicle as PM. Using the β and μ values from the SAS OP procedure based on the 720 dollars as PM presented in Table 17, the probabilities were calculated three years from the present. This was done in three steps. In each step, the age and mileage were increased to reflect those properties.

The predicted probabilities and weighted probabilities for those vehicles for the following 12 months are presented in Table 24. Thereafter, in order to predict a vehicle's condition state 24 months later, 12 months were added to the vehicle’s current age, and average running mileage were added to the current mileage. Applying the same coefficients as in Table 17, the predicted condition states and weighted probabilities at the end of the second year are presented in Table 25. Similarly, those vehicles’ age and mileage were changed again to get the probabilities after 36 months. The vehicle parameters were again adjusted and the predicted probabilities are in Table 26. The arithmetic average value of weighted probability is presented in the last row of each predicted probabilities table. For example, the average weighted probability is 306.38 in Table 24.

Table 24. Predicted probabilities for vehicles at the end of year 1 (PM = $720)

Vehicle	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
1	46.74	43.85	9.30	0.10	0.00	162.76
2	82.35	16.65	1.00	0.00	0.00	118.66
3	3.49	30.41	57.41	8.38	0.31	271.61
4	0.38	9.73	59.04	27.83	3.02	323.39
5	5.94	37.63	51.10	5.19	0.14	255.97
6	0.04	2.30	39.24	46.22	12.20	368.25
7	0.10	4.40	48.69	39.57	7.25	349.47
8	3.22	29.38	58.13	8.92	0.34	273.77
9	0.00	0.30	16.35	49.24	34.10	417.13
10	0.00	0.16	11.88	46.06	41.90	429.70
11	3.19	29.24	58.23	9.00	0.35	274.08
12	0.00	0.14	11.21	45.38	43.27	431.77
Avg.						**306.38**

Table 25. Predicted probabilities for vehicles at the end of year 2 (PM = $720)

Vehicle	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
1	65.68	30.74	3.56	0.02	0.00	137.91
2	97.44	2.51	0.04	0.00	0.00	102.60
3	19.84	51.07	28.09	0.99	0.01	210.26
4	3.82	31.58	56.54	7.79	0.27	269.12
5	35.44	49.28	15.03	0.25	0.00	180.10
6	0.86	15.37	62.31	19.95	1.51	305.88
7	3.70	31.19	56.84	7.98	0.28	269.96
8	38.25	48.16	13.39	0.20	0.00	175.54
9	0.14	5.56	52.03	36.48	5.79	342.21
10	0.05	2.98	42.96	43.93	10.08	361.01
11	75.39	22.75	1.85	0.01	0.00	126.47
12	1.02	16.82	62.51	18.37	1.28	302.08
Avg.						**231.93**

Table 26. Predicted probabilities for vehicles at the end of year 3 (PM = $720)

Vehicle	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
1	81.31	17.58	1.11	0.00	0.00	119.80
2	99.85	0.15	0.00	0.00	0.00	100.15
3	54.72	38.81	6.42	0.05	0.00	151.80
4	19.17	50.90	28.87	1.06	0.01	211.85
5	79.19	19.46	1.35	0.00	0.00	122.17
6	8.38	42.34	45.63	3.57	0.08	244.61
7	31.59	50.50	17.55	0.35	0.00	186.67
8	89.45	10.15	0.40	0.00	0.00	110.95
9	3.47	30.34	57.46	8.41	0.31	271.75
10	1.38	19.69	62.36	15.62	0.94	295.04
11	99.94	0.06	0.00	0.00	0.00	100.06
12	39.84	47.46	12.53	0.18	0.00	173.05
Avg.						**173.99**

This study was conducted two more times with all variables constant except that the annual PM values were reduced to 360 and 72 dollars, respectively. The predicted probabilities at the end of the third year are presented in Table 27 and 28. The summation of average weighted probabilities of the fleet is shown in Table 29 and plotted as a function of time in Figure 24.

Table 27. Predicted probabilities for vehicles at the end of year 3 (PM = $360)

Vehicle	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=4	Prob CS=4	Weighted Prob
1	96.74	3.20	0.06	0.00	0.00	103.32
2	100.00	0.00	0.00	0.00	0.00	100.00
3	85.83	13.49	0.67	0.00	0.00	114.84
4	53.29	39.78	6.88	0.06	0.00	153.71
5	96.14	3.78	0.08	0.00	0.00	103.94
6	33.52	49.94	16.24	0.30	0.00	183.32
7	68.27	28.68	3.04	0.01	0.00	134.80
8	98.63	1.36	0.02	0.00	0.00	101.39
9	19.45	50.97	28.54	1.03	0.01	211.17
10	10.61	45.37	41.32	2.66	0.05	236.16
11	100.00	0.00	0.00	0.00	0.00	100.00
12	75.70	22.49	1.80	0.01	0.00	126.11
Avg.						**139.06**

Table 28. Predicted probabilities for vehicles at end of year 3 (PM = $72)

Vehicle	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=4	Prob CS=4	Weighted Prob
1	99.54	0.45	0.00	0.00	0.00	100.46
2	100.00	0.00	0.00	0.00	0.00	100.00
3	96.68	3.26	0.06	0.00	0.00	103.38
4	80.12	18.64	1.24	0.00	0.00	121.13
5	99.43	0.57	0.00	0.00	0.00	100.57
6	63.23	32.64	4.11	0.02	0.00	140.93
7	89.23	10.36	0.42	0.00	0.00	111.19
8	99.85	0.15	0.00	0.00	0.00	100.15
9	46.10	44.22	9.57	0.10	0.00	163.68
10	31.41	50.54	17.68	0.36	0.00	186.99
11	100.00	0.00	0.00	0.00	0.00	100.00
12	92.79	7.00	0.21	0.00	0.00	107.43
Avg.						**119.66**

Table 29. Average weighted predicted probabilities as PM varies

Year/PM	$72	$360	$720
1	210.55	251.41	306.38
2	154.1	185.03	231.93
3	119.66	139.06	173.99

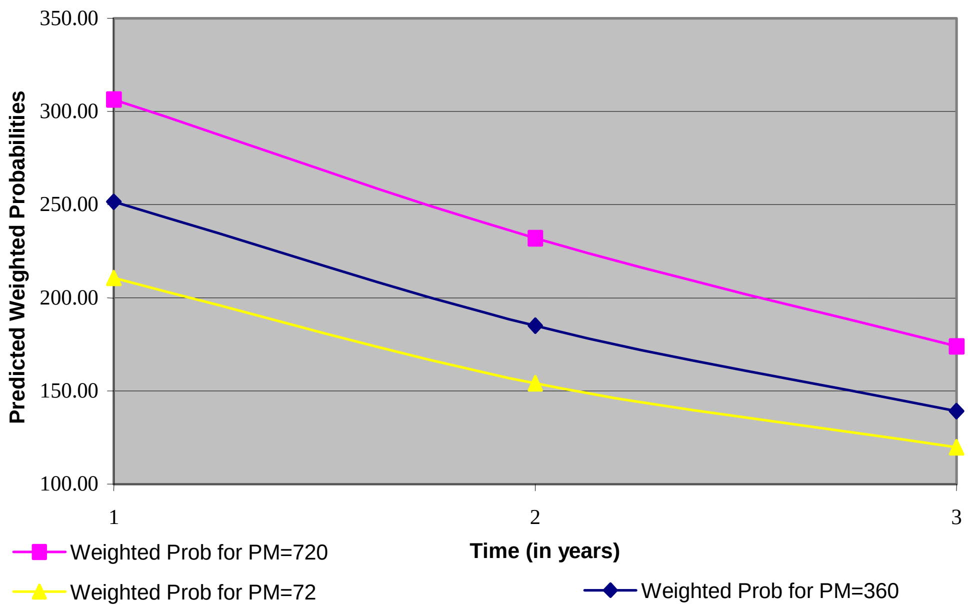

Figure 24. Predicted weighted probabilities for various maintenance strategies

In all cases, the average weighted probability falls over time in Figure 24. When comparing preventive maintenance strategies, it is obvious that as the resources devoted to preventive maintenance are reduced, the condition of each vehicle, and the entire fleet, decreases. This conclusion was made by observing the probabilities of each vehicle and its corresponding weighted probabilities.

It is valuable for fleet managers to know how much to allocate budgets to bring the fleet up to the same conditions as spending more on PM annually after a period of time. To bring weighted probabilities of the fleet using the alternative preventive maintenance strategies to the value observed for the baseline PM policy, the agency will need to spend considerable future resources. In the model, this is accomplished by increasing the CM costs in the last iteration until the predicted probabilities for each vehicle was equal to those at the end of the third iteration using the baseline preventive maintenance strategy.

For example, if PM is currently 360 dollars, additional expenditures have to be allocated for CM to maintain the vehicle 3 years later to make it have similar conditions as spending 720 dollars annually doing PM. To know that amount in advance is very helpful. Therefore, in the third year, the present value of the CM cost and total maintenance cost, applying 6 percent inflation rate, is shown in Table 30 and Figure 25. After that, the average weighted probabilities of the entire fleet matched those of the baseline (720 dollars annually as PM) policy. The calculation procedures for CM are illustrated as follows.

Table 30. Present value of the three maintenance strategies

Vehicle	720/yr	CM when PM= 720/yr	Total 1 720/yr +CM	360/yr	CM when PM = 360/yr	Total 2 360/yr +CM	72/yr	CM when PM= 72/yr	Total 3 72/yr +CM
1	2040	0	2040	1020	2229	3249	204	4013	4217
2	2040	0	2040	1020	1998	3018	204	4005	4209
3	2040	0	2040	1020	2229	3249	204	4013	4217
4	2040	0	2040	1020	2229	3249	204	4013	4217
5	2040	0	2040	1020	2233	3253	204	4013	4217
6	2040	0	2040	1020	2230	3250	204	4013	4217
7	2040	0	2040	1020	2229	3249	204	4013	4217
8	2040	0	2040	1020	2230	3250	204	4013	4217
9	2040	0	2040	1020	2229	3249	204	4013	4217
10	2040	0	2040	1020	2230	3250	204	4013	4217
11	2040	0	2040	1020	2149	3169	204	4013	4217
12	2040	0	2040	1020	2230	3250	204	4014	4218

Note: All costs are in dollars. Time span is 3 years.

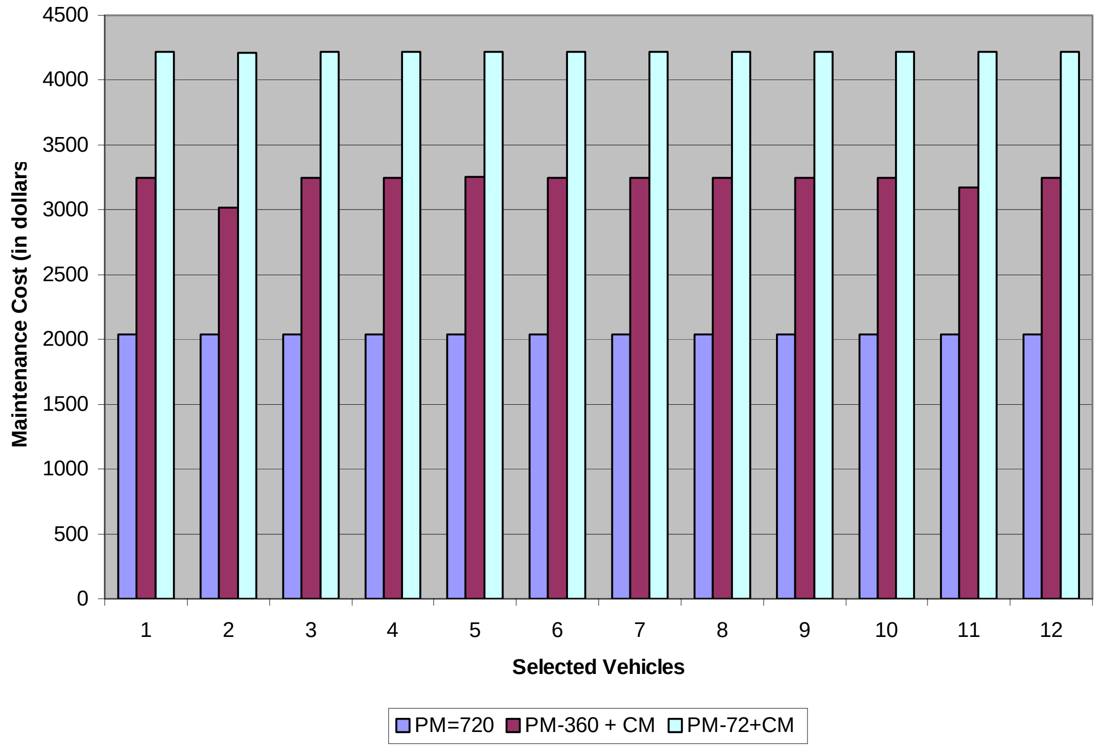

Figure 25. Present value of total maintenance costs over three years

To illustrate the computing procedure, the first vehicle in Table 23 was selected. To predict its future condition 12 months later, its age and mileage has to be justified. Since the average running mileage per year for this vehicle based on the historical available records is about 14,626 miles, the mileage of the vehicle is about 227,462 miles 36 months later and its age increases to 187 months.

From the explanation of the OP model in chapter 3, in order to have similar probabilities when PM is 360 dollars as those when PM is 720 dollars, since β and μ are constant, β X should be very close. β is the estimated coefficient and X is the predictor vector. The β X of spending 360 dollars per year in preventive maintenance is

$$\beta = \begin{pmatrix} -0.0045173 \\ 0.0000369 \\ -0.0026507 \\ -0.0003593 \end{pmatrix} \quad \mathrm{X} = \begin{pmatrix} 187 & 227462 & 360 & y \end{pmatrix}$$

Hence,

$$\beta\,\mathrm{X} = 6.5943607 - 0.0003593y \tag{7}$$

The β X of spending 720 dollars per year in preventive maintenance is

$$X' = \begin{pmatrix}187 & 227462 & 720 & 0\end{pmatrix}$$

Therefore,

$$\beta X' = 5.640109 \tag{8}$$

While y is the corrective maintenance cost that is unknown. Set equation 7 equal to equation 8, then y can be solved.

$$5.640109 = 6.5943607 - 0.0003593y$$

$$\therefore y \approx \$2656$$

Assume the inflation rate is 6 percent every year; the additional maintenance cost was discounted to the current value by applying equation 7, and the present value is 2,229 dollars.

$$\text{Present Value} = \text{Future Value} / (1 + r)^t, \tag{9}$$

where r is interest rate and t is time period measured in years.

Similarly, apply equation 5-3 to 360 and 720 dollars 24 and 36 months later, the present values are about 1,020 and 2,040 dollars, which is shown in columns “CM 360/yr” and “CM 720/yr” in Table 30. The “Total i” column is the summation of the present values representing the total spending on maintenance.

$$\$360 + \$360/1.06 + \$360/1.06^2 = \$1,020 \tag{10}$$

$$\$720 + \$720/1.06 + \$720/1.06^2 = \$2,040 \tag{11}$$

Therefore, in the next 36 months, the compensation for switching from currently 360 dollars to 720 dollars per year as preventive maintenance is about 2,229 dollars. To that specific vehicle, if 360 dollars were spent every year doing routine maintenance, its probability of being in condition state 1 three years later is about 3.20 percent, shown in Table 27. However, after spending 2,556 dollars doing corrective maintenance 36 months later, the probability of being in condition state 1 is the same as spending 720 dollars doing preventive maintenance, which is about 17.58 percent. From the procedure above, the compensation amount can be calculated.

When this was done, the CM costs were found to be about 2,229 and 4,217 dollars for the 360 and 72 dollars annual preventive maintenance policies, respectively.

From the analysis above, the OP method can be used to study the impact of different maintenance strategies. In this study, the impact of reducing the preventive maintenance budget over a period of time and then increasing it to maintain the fleet at the base line service level can be very expensive. The old saying “Pay me now or pay me later” makes real sense in this study.

Impact of Preventive Maintenance

Instead of varying PM under the maintenance policy discussed above, it is more valuable to observe the weighted probabilities to know the fleet performance under different maintenance strategies by observing vehicle performance under a series of maintenance plans to identify a cost-effective maintenance strategy. Different from the first analysis, which was conducted on one data set containing an existing maintenance policy, a total of 19 different data sets were considered in the study that follows.

In previous analyses, when the comparison was made, the coefficients β and μ were not allowed to vary as different annual PM values were considered. In this study, all the other parameters, for instance, vehicle age and mileage, were held constant but the PM expenditures were allowed to vary from 72 to 1500 dollars, as shown in Table 11. Each data set was entered into SAS OP model and the corresponding set of estimated coefficients were calculated. Thus, this study utilized a total of 19 sets of β 's and μ 's. Three vehicles in different conditions were considered for evaluation. The properties of these vehicles can be found in Table 31. Each one of them represents a group of vehicles in similar condition state, which varies from 1 to 3. The PM varies since different maintenance strategies are involved.

Table 31. Selected vehicles for evaluation

Vehicle ID	CS	Age	Mileage	PM	CM
1	1	80	150000	Varies	0
2	2	43	88037	Varies	0
3	3	21	44000	Varies	0

The proposed methodology needs different data sets from different transit agencies with different maintenance strategies. But those data sets are not available in this study. Therefore, the data sets refined previously were used to pursue the study to demonstrate the methodology. If more real data are available, the results will change but the method is still usable. Following the previous procedures, each data set was inputted to SAS OP procedure to get estimated β 's and μ 's listed in Table 32.

Table 32. Calculated coefficients by SAS/OP model with various PMs

PM	Age	Mileage	PM	CM	μ_0	μ_1	μ_2	μ_3
72	0.003922	1.71E-05	0.01439	-5.4E-05	-4.59124	-3.56494	-2.33159	-1.13129
80	0.002019	2.06E-05	0.001388	-6.4E-05	-4.06551	-3.00544	-1.73601	-0.58335
90	0.000104	2.43E-05	-0.0071	-9.3E-05	-3.79895	-2.69064	-1.36302	-0.22585
103	-0.00155	2.78E-05	-0.01172	-0.00014	-3.73070	-2.56645	-1.16537	-0.01822
120	-0.00279	3.06E-05	-0.0132	-0.00018	-3.80304	-2.58395	-1.10521	0.06900
144	-0.00364	3.29E-05	-0.01262	-0.00023	-3.95917	-2.68926	-1.13344	0.07860
180	-0.00415	3.45E-05	-0.01075	-0.00027	-4.15607	-2.84292	-1.21731	0.03722
240	-0.00441	3.56E-05	-0.00821	-0.00031	-4.36368	-3.01535	-1.32984	-0.03213
360	-0.00452	3.64E-05	-0.00543	-0.00034	-4.56471	-3.18851	-1.45333	-0.11421
480	-0.00453	3.67E-05	-0.00403	-0.00035	-4.6599	-3.27214	-1.51571	-0.15697
720	-0.00452	3.69E-05	-0.00265	-0.00036	-4.75081	-3.35285	-1.57733	-0.19981
800	-0.00451	3.69E-05	-0.00238	-0.00036	-4.76843	-3.36857	-1.58944	-0.20822
900	-0.00451	3.7E-05	-0.00211	-0.00036	-4.78591	-3.38422	-1.60163	-0.21685
1080	-0.0045	3.7E-05	-0.00175	-0.00037	-4.80891	-3.40484	-1.61771	-0.22816
1100	-0.0045	3.7E-05	-0.00172	-0.00037	-4.81097	-3.40667	-1.61911	-0.2291
1200	-0.0045	3.71E-05	-0.00157	-0.00037	-4.82029	-3.41505	-1.6257	-0.23379
1300	-0.0045	3.71E-05	-0.00145	-0.00037	-4.82813	-3.42211	-1.63126	-0.23776
1400	-0.00449	3.71E-05	-0.00134	-0.00037	-4.83479	-3.42808	-1.6359	-0.24096
1500	-0.00449	3.71E-05	-0.00125	-0.00037	-4.84056	-3.43328	-1.64001	-0.2439

Once the corresponding β and μ coefficients were calculated, they were inputted to a spreadsheet to calculate the predicted probabilities for each condition state at the end of year. The weighted probability was used to measure the impact of the variables.

The predicted probabilities for vehicles 1, 2, and 3 are presented in Tables 33, 34, and 35, respectively. Those probabilities are plotted for these vehicles in Figures 26, 28, and 30, respectively. Finally, the weighted probabilities are plotted in Figures 27, 29, and 31 for those three vehicles.

Table 33. Predicted probabilities for vehicle 1 when PM varies

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	24.94	38.74	30.65	5.40	0.27	217.32
80	24.01	39.83	30.94	4.95	0.27	217.64
90	21.68	41.07	32.33	4.65	0.26	220.71
103	18.53	42.07	34.65	4.50	0.24	225.82
120	15.46	42.55	37.35	4.42	0.22	231.39
144	12.75	42.48	40.19	4.39	0.19	236.79
180	10.58	41.96	42.90	4.40	0.16	241.60
240	8.97	41.26	45.23	4.40	0.14	245.48
360	7.77	40.45	47.24	4.42	0.12	248.67
480	7.29	40.05	48.11	4.44	0.12	250.08
720	6.87	39.64	48.92	4.46	0.11	251.30
800	6.79	39.56	49.07	4.47	0.11	251.55
900	6.73	39.50	49.20	4.47	0.11	251.76
1080	6.64	39.41	49.38	4.47	0.10	251.98
1100	6.62	39.38	49.42	4.47	0.10	252.02
1200	6.59	39.35	49.49	4.47	0.10	252.14
1300	6.55	39.30	49.57	4.48	0.10	252.28
1400	6.53	39.29	49.60	4.47	0.10	252.29
1500	6.51	39.27	49.65	4.48	0.10	252.42

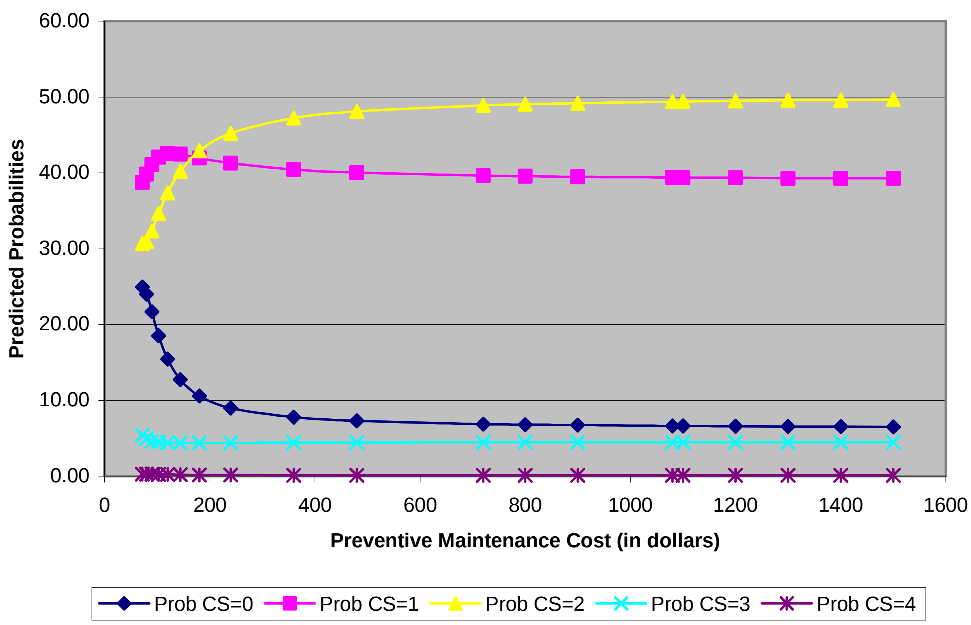

Figure 26. Predicted probability trend for vehicle 1 when PM varies

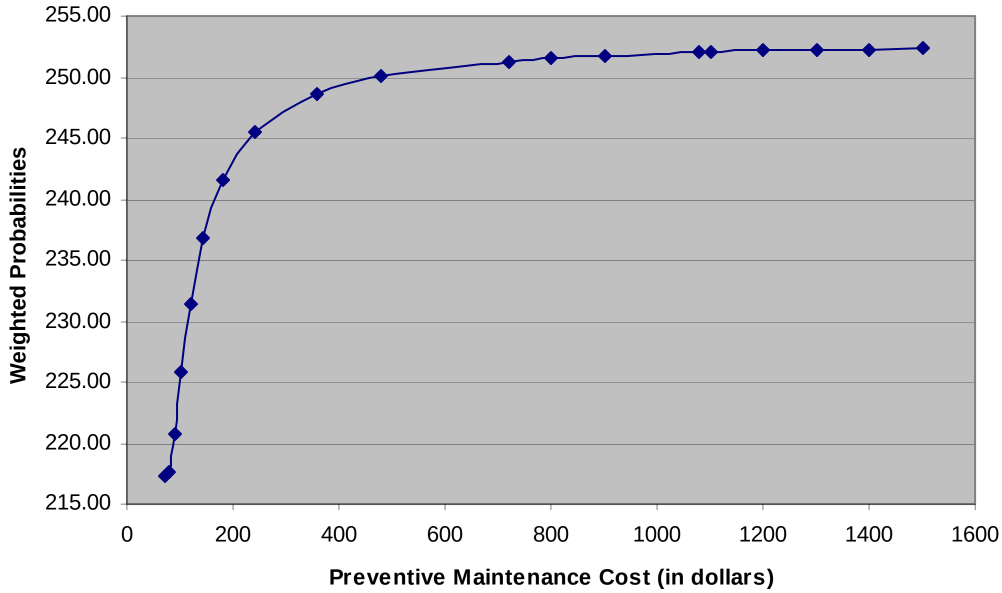

Figure 27. Weighted probability trend for vehicle 1 when PM varies

Table 34. Predicted probabilities for vehicle 2 when PM varies

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Porb CS=4	Weighted Prob
72	3.00	16.64	45.12	29.53	5.72	318.34
80	1.99	13.98	44.81	31.53	7.69	328.95
90	1.09	10.71	43.87	34.30	10.03	341.46
103	0.53	7.65	42.14	37.28	12.40	353.38
120	0.25	5.32	39.92	40.07	14.44	363.13
144	0.12	3.72	37.68	42.56	15.92	370.44
180	0.06	2.68	35.68	44.73	16.85	375.62
240	0.04	2.04	34.12	46.56	17.25	378.94
360	0.02	1.62	32.89	48.13	17.33	381.12
480	0.02	1.47	32.39	48.84	17.28	381.89
720	0.02	1.35	31.94	49.49	17.21	382.52
800	0.02	1.33	31.86	49.61	17.18	382.62
900	0.01	1.31	31.79	49.73	17.16	382.70
1080	0.01	1.28	31.70	49.89	17.12	382.81
1100	0.01	1.28	31.68	49.91	17.12	382.85
1200	0.01	1.27	31.64	49.97	17.11	382.89
1300	0.01	1.26	31.60	50.02	17.11	382.95
1400	0.01	1.25	31.59	50.07	17.08	382.95
1500	0.01	1.25	31.56	50.10	17.07	382.94

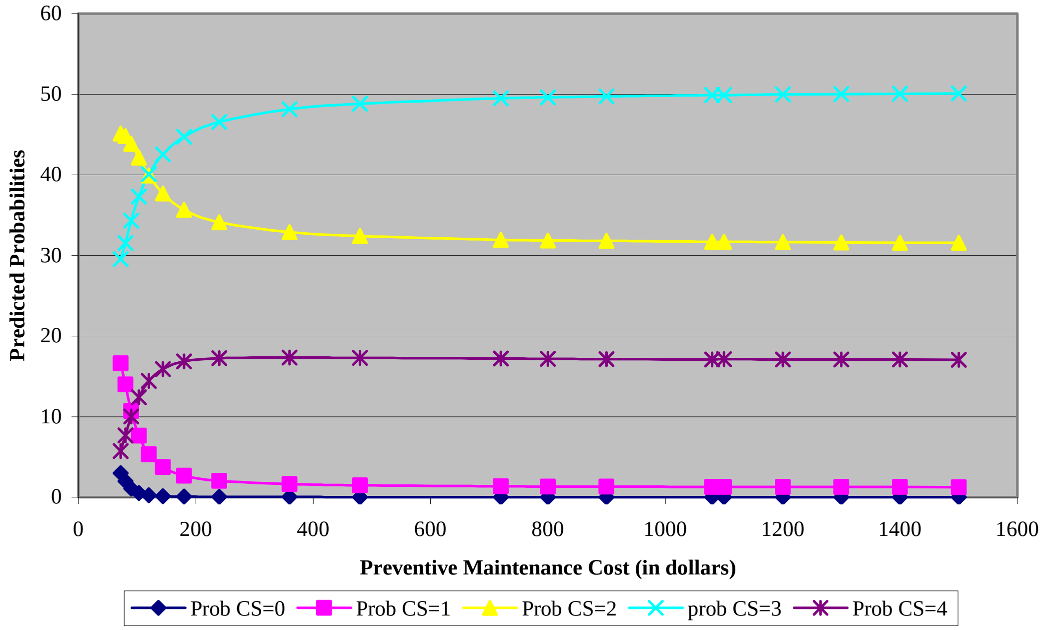

Figure 28. Predicted probability trend for vehicle 2 when PM varies

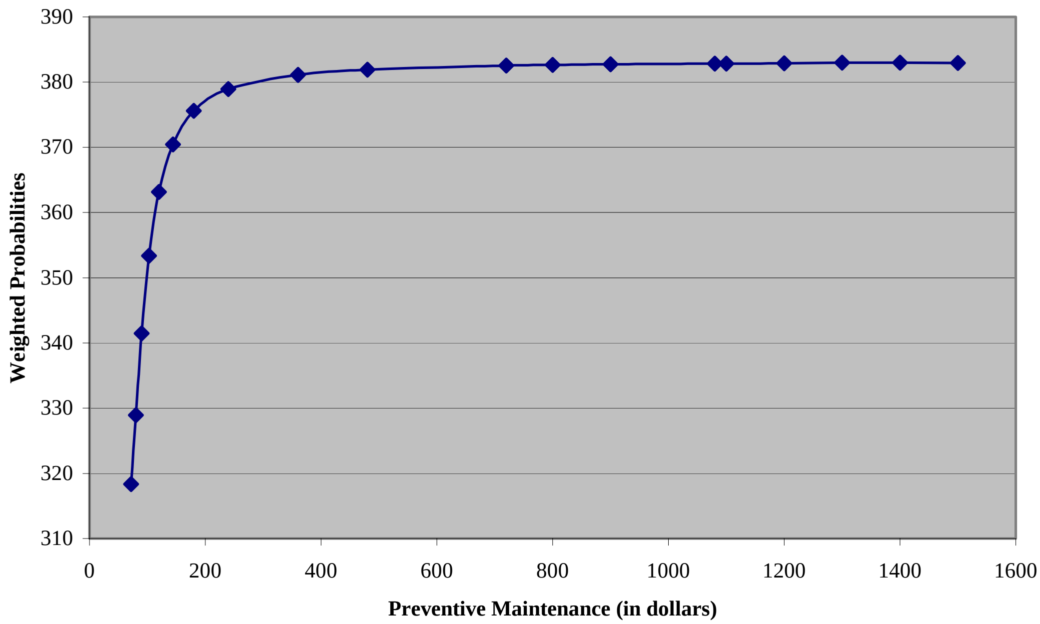

Figure 29. Weighted probability trend for vehicle 2 when PM varies

Table 35. Predicted probabilities for vehicle 3 when PM varies

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4	Weighted Prob
72	0.33	4.19	27.74	47.77	22.98	397.91
80	0.13	2.45	22.34	43.36	31.72	404.09
90	0.04	1.16	16.42	40.59	41.80	422.98
103	0.01	0.48	11.35	36.73	51.42	439.04
120	0.00	0.20	7.87	32.98	58.95	450.68
144	0.00	0.08	5.61	29.91	64.40	458.63
180	0.00	0.04	4.21	27.76	67.99	463.70
240	0.00	0.02	3.38	26.5	70.11	466.73
360	0.00	0.01	2.85	25.83	71.30	468.39
480	0.00	0.01	2.66	25.67	71.65	468.93
720	0.00	0.01	2.51	25.59	71.89	469.36
800	0.00	0.01	2.48	25.59	71.92	469.42
900	0.00	0.01	2.46	25.59	71.95	469.51
1080	0.00	0.01	2.42	25.59	71.97	469.49
1100	0.00	0.01	2.42	25.59	71.98	469.54
1200	0.00	0.01	2.41	25.59	71.99	469.56
1300	0.00	0.01	2.40	25.59	72.01	469.63
1400	0.00	0.01	2.39	25.60	72.01	469.64
1500	0.00	0.01	2.38	25.60	72.01	469.65

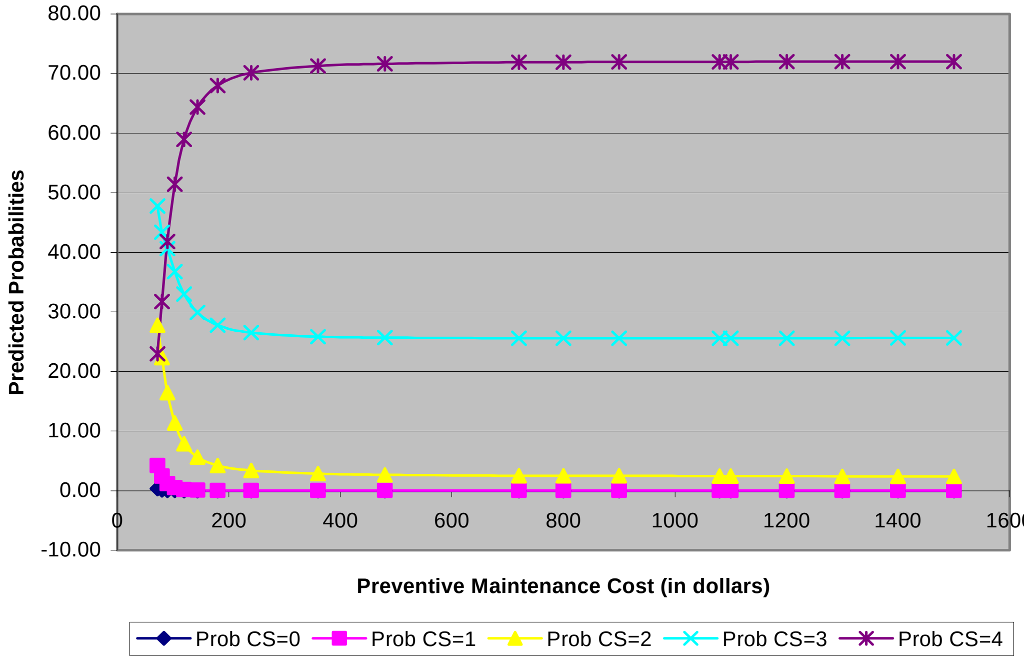

Figure 30. Predicted probability trend for vehicle 3 when PM varies

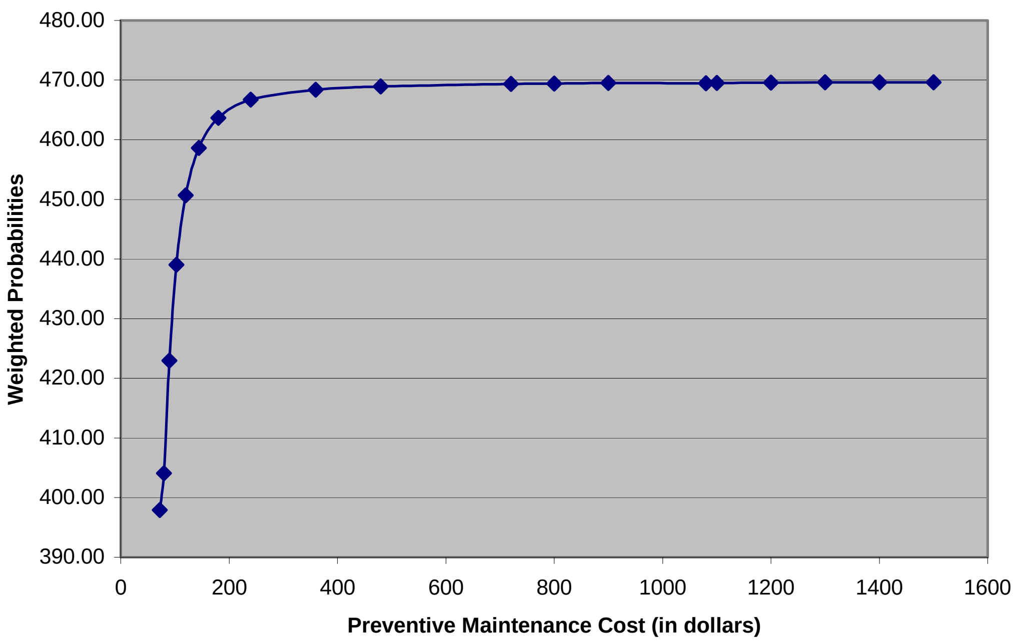

Figure 31. Weighted probability trend for vehicle 3 when PM varies

This study demonstrates that under the existing maintenance plan, as PM for vehicles in different condition states increases, vehicle performance increases also. If maintenance policies change, the impact of PM on predicted condition states is presented in the following section.

While it is tempting to compare the results of previous analyses with this one, there are considerable differences. In the previous analyses, PM was held constant when calculating β and μ values by OP method. After β and μ were estimated, they were held constant and PM values were allowed to vary. This condition is appropriate when looking for a relatively short-term impact of a change in the preventive maintenance funds.

In this study, the preventive maintenance values are assumed to vary for the basic fleet and, therefore, β and μ values are recalculated for each preventive maintenance value. From those charts above, fleet managers can see the current fleet condition compares with other maintenance strategies. When addition funding is available for doing PM, the vehicles may increase their performance dramatically or may not change much, depends on current existing PM values.

For OP method to work best, long-term data on fleet conditions is vital for a wide range of agencies with different maintenance strategies. While the original intent of this research was to obtain this type of data, it was not possible with the resources allocated to this project. However, it would have been very useful and would add significant strength to this research.

Marginal Effects of Preventive Maintenance

Marginal effects reflect the change in the probability of a vehicle being in a condition state due to a unit change in a predictor. It can be directly applied to management decision-making. For example, as discussed previously, when more funds are available, it is valuable to know how much predicted probabilities are going to change if they are invested on PM, which cannot be implied by observing the weighted probability chart but can be implied by observing the marginal effect chart.

To obtain the marginal effects of different maintenance policies, the first derivative of the OP model's Maximum Likelihood function is required. The formulas were presented in an earlier section. MatLab is used to calculate marginal effects since it has a stronger ability to handle matrix. The source code of the calculation done in MatLab can be found in Appendix C. β's and μ's in Table 28 were used to calculate marginal effects. Nineteen totally different data sets were used to obtain the marginal effects of PM. The marginal effects, the variation of predicted probabilities in each condition state due to unit increase of PM, to vehicles from Table 31 are presented in Tables 36, 37, and 38, and plotted in Figures 32, 33, and 34 separately for three different vehicles. Figure 35 is a partial enlarged chart of Figure 33.

From Table 36, if one more dollar was spent on PM when current annual PM amounts is 720 dollars, the predicted probability of being in condition state 4 increases 0.0893 percent. However, from the previous study, marginal effect is not a linear function of PM. Therefore, the marginal effect chart is helpful to compare the efficiency of additional investments.

From observation of Figures 32, 33, and 34, PM's marginal effect first goes up then goes down and tends to approach a limit. For example, from Figure 35, the probability increment of being in condition state 3 and 4 first grows quickly before the PM reaches 144 dollars, then declines. Hence, the highest marginal effect point may exist. Due to the limited available data, further study could not be conducted. Other observation of vehicle 1 and 3 in Table 18 generates similar results.

Table 36. Marginal effect of PM on vehicle 1

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4
72	0.0145	0.1239	0.3796	-0.0836	-0.4344
80	0.0006	0.0077	0.0357	0.0054	-0.0494
90	-0.0010	-0.0210	-0.1612	-0.0943	0.2774
103	-0.0004	-0.0159	-0.2143	-0.2365	0.4672
120	-0.0001	-0.0081	-0.1875	-0.3168	0.5125
144	0.0000	-0.0036	-0.1392	-0.3264	0.4692
180	0.0000	-0.0015	-0.0949	-0.2807	0.3835
240	0.0000	-0.0007	-0.0608	-0.2229	0.2844
360	0.0000	-0.0003	-0.0351	-0.1493	0.1847
480	0.0000	-0.0002	-0.0246	-0.1115	0.1363
720	0.0000	-0.0001	-0.0154	-0.0738	0.0893
800	0.0000	-0.0002	-0.0195	-0.0682	0.0879
900	0.0000	-0.0001	-0.0121	-0.0588	0.0710
1080	0.0000	-0.0001	-0.0099	-0.0489	0.0589
1100	0.0000	-0.0001	-0.0097	-0.0480	0.0578
1200	0.0000	-0.0001	-0.0089	-0.0439	0.0528
1300	0.0000	0.0000	-0.0081	-0.0405	0.0487
1400	0.0000	0.0000	-0.0075	-0.0376	0.0452
1500	0.0000	0.0000	-0.0070	-0.0351	0.0421

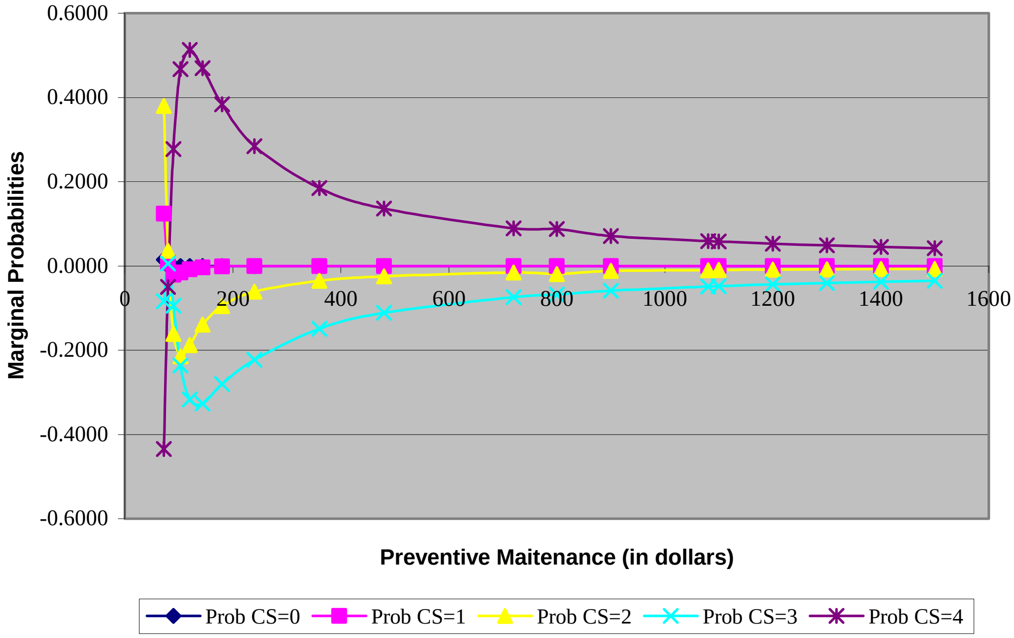

Figure 32. Marginal effect chart for vehicle 1

Table 37. Marginal effect of PM on vehicle 2

PM	Prob CS=0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4
72	0.0979	0.3005	0.1360	-0.3693	-0.1651
80	0.0067	0.0270	0.0196	-0.0333	-0.0200
90	-0.0204	-0.1199	-0.1400	0.1555	0.1249
103	-0.0178	-0.1594	-0.2904	0.2276	0.2399
120	-0.0101	-0.1381	-0.3752	0.2231	0.3003
144	-0.0050	-0.1002	-0.3869	0.1860	0.3060
180	-0.0023	-0.0656	-0.3428	0.1402	0.2705
240	-0.0011	-0.0399	-0.2667	0.0980	0.2097
360	-0.0005	-0.0218	-0.1779	0.0610	0.1391
480	-0.0003	-0.0149	-0.1322	0.0441	0.1033
720	-0.0002	-0.0091	-0.0871	0.0287	0.0676
800	-0.0001	-0.0081	-0.0782	0.0257	0.0606
900	-0.0001	-0.0070	-0.0693	0.0228	0.0536
1080	-0.0001	-0.0057	-0.0575	0.0189	0.0444
1100	-0.0001	-0.0056	-0.0564	0.0185	0.0436
1200	-0.0001	-0.0051	-0.0516	0.0169	0.0399
1300	-0.0001	-0.0047	-0.0476	0.0156	0.0368
1400	-0.0001	-0.0043	-0.0441	0.0145	0.0341
1500	-0.0001	-0.0040	-0.0411	0.0135	0.0318

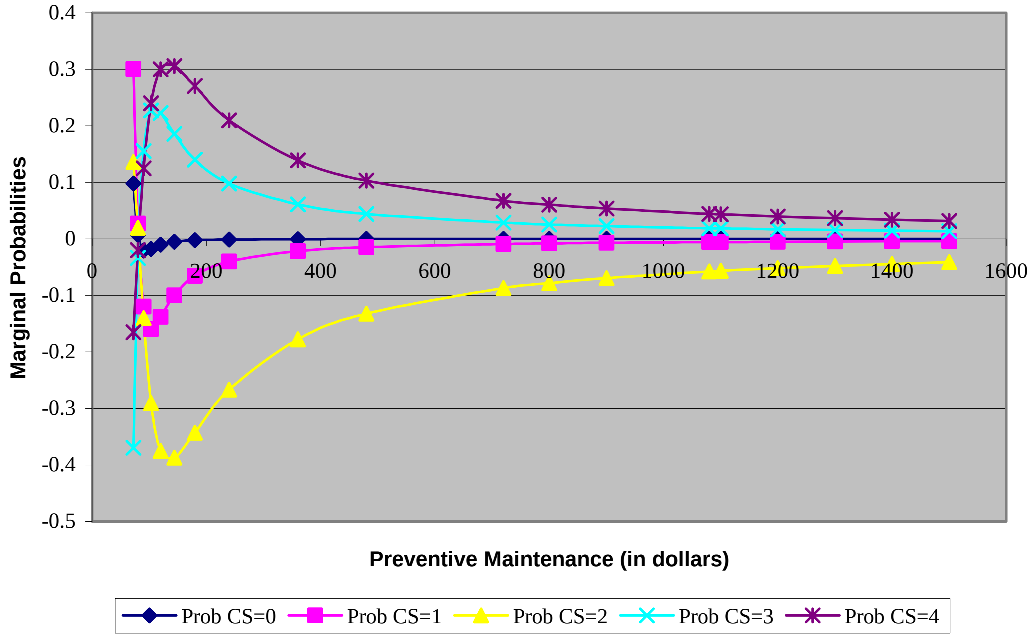

Figure 33. Marginal effect chart for vehicle 2

Table 38. Marginal effect of PM on vehicle 3

PM	Prob CS= 0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4
72	0.4589	0.0797	-0.3765	-0.1504	-0.0177
80	0.0432	0.0088	-0.0372	-0.0136	-0.0012
90	-0.2079	-0.0611	0.1963	0.0669	0.0058
103	-0.3115	-0.1401	0.3346	0.1081	0.0090
120	-0.3119	-0.2048	0.3870	0.1205	0.0091
144	-0.2615	-0.2380	0.3770	0.1149	0.0077
180	-0.1952	-0.2330	0.3242	0.0982	0.0057
240	-0.1322	-0.1953	0.2486	0.0751	0.0038
360	-0.0786	-0.1378	0.1642	0.0499	0.0022
480	-0.0557	-0.1047	0.1217	0.0372	0.0016
720	-0.0350	-0.0703	0.0798	0.0245	0.0010
800	-0.0406	-0.0538	0.0781	0.0158	0.0005
900	-0.0274	-0.0563	0.0634	0.0195	0.0008
1080	-0.0225	-0.0469	0.0526	0.0162	0.0006
1100	-0.0220	-0.0461	0.0516	0.0159	0.0006
1200	-0.0201	0.0422	0.0472	0.0146	0.0005
1300	-0.0184	-0.0390	0.0435	0.0134	0.0005
1400	-0.0171	-0.0362	0.0403	0.0124	0.0005
1500	-0.0159	-0.0338	0.0376	0.0116	0.0004

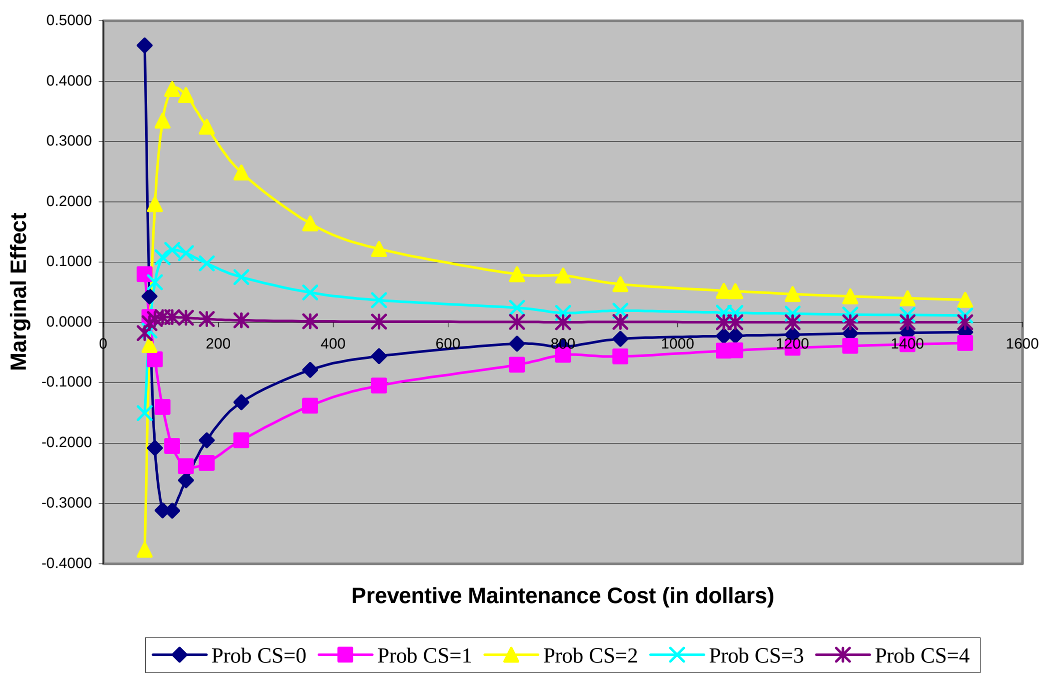

Figure 34. Marginal effect chart for vehicle 3

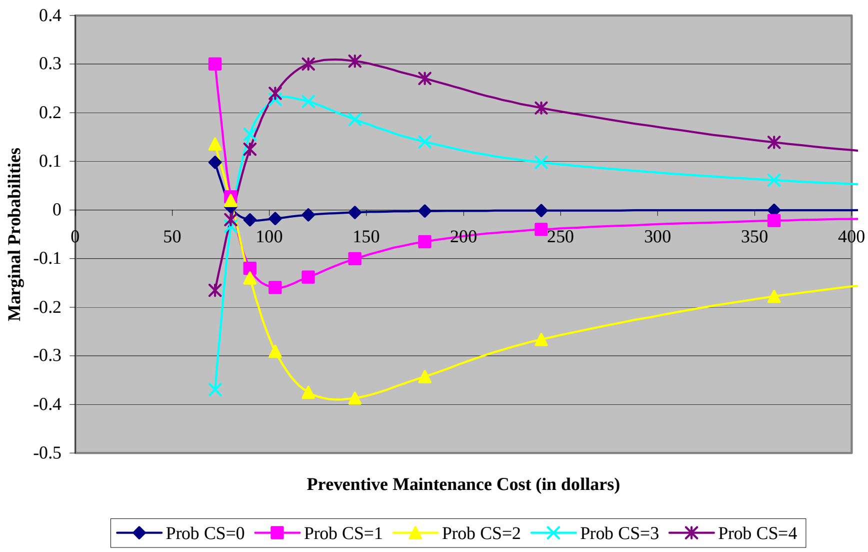

Figure 35. Partial enlarged marginal effect chart for vehicle 2

Verify Critical Predictors by Marginal Effects

Marginal effect can also be used to identify the critical predictors. From the study in previous chapters, critical predictors were identified by partial, semi-partial correlation analysis, and p-value of predicted coefficients by SAS OP model. By comparing the marginal effect of different predictors, one can also identify the critical ones. For example, in Table 39, marginal effects of mileage and PM are presented to vehicle 2 when PM was 720 dollars annually.

Table 39. Marginal effect of predictors (vehicle 2, PM=$720)

	Prob CS= 0	Prob CS=1	Prob CS=2	Prob CS=3	Prob CS=4
Mileage	0.0000	0.00012	0.0012	-0.0004	-0.0010
PM	-0.0002	-0.0091	-0.0871	0.0287	0.0676

The absolute value of marginal effect of PM is always higher than that of mileage. For instance, the marginal effect's absolute value of PM on predicted probability of staying in condition state 4 is 0.0676 percent, which is higher than that of mileage, which is 0.0010. This reveals that routine maintenance cost contributes more to the change of the condition states than mileage does. Therefore, by comparing the absolute value of predictors' marginal effects, one is able to identify and verify critical predictors.

In Table 33, the marginal effect of being in condition state 4 decreases as PM increases when PM is 72 and 80 dollars per year. That is not quite reasonable due to the assumption of the wide range of PM. From that one can also identify the unreasonable PM values.

CONCLUSIONS

This study developed a methodology for improving the practice of making transit asset investment decisions at state DOTs and local transit agencies. The results of a literature review indicated that the majority of studies find that there are significant differences in vehicle operating costs between road types (i.e., bituminous versus gravel versus earth), age, mileage, and vehicle type. Vehicle repair/maintenance cost is found to be primarily affected by vehicle condition. In terms of non-vehicle operating costs, vehicle downtime due to maintenance work and road calls due to vehicle breakdowns on the road were extensively studied in relation to vehicle condition.

The major capability of the new vehicle deterioration model developed under this study is to predict the future conditions of the vehicle based on the historical records of the selected dependent factors, such as the vehicle's age, mileage, current conditions, and so forth. The contribution of possible variables was analyzed and the factors that affect the vehicle's future conditions were specified. The model can identify the relative importance of the independent variables with the given condition ratings shown. In addition, predictions can be made for the individual vehicles or a group of vehicles at different condition ratings, both of which are important for the management system. Knowing the percentages of vehicles at different condition ratings in the future based on the present and historical conditions, a transit fleet manager can allocate the budget more efficiently and accurately.

This study also developed relationships between vehicle conditions and the cost of preventive and corrective maintenance and a life cycle cost analysis (LCCA) methodology incorporating these cost relationships into network level and project level decisions. One can use these relationships and LCCA to select the best maintenance strategies for short- and long-term operation. The models can help in making decisions about which applicable maintenance to use on the basis of minimizing total cost. The software developed implementing this system is called RSUTAMS. RSUTAMS is generic in nature and employs a visual interface that allows users to customize it to suit their particular transit asset management database structure and practice through a series of models.

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APPENDIX A

Transit Asset Management System (RSUTAMS)

Transit Asset Management System (RSUTAMS)

RSUTAMS consists of the following five modules:

1. Data input and management
2. Short-term maintenance decision making
3. Life cycle cost analysis for long-term planning
4. Decision making and updating of maintenance and replacement schedule
5. The RSUTAMS is specially designed to be adaptable to the practices of State DOT and various local transit agencies. Microsoft Visual Basic was used as the major programming language for developing interface and analysis functions, and Microsoft Access was used for the database storage and processing.

Data Input and Management Module

This module is an essential component of RSUTAMS because they allow the user to input the general and particular characteristics of transit asset through a series of screens. The database is organized in the following tables:

1. Asset inventory
2. Asset condition and maintenance
3. Asset classification
4. Asset treatment alternatives
5. Unit costs for the agency

The majority of these screens contain default input values, which can be overridden by the user. All screen input is associated with specific tables.

Vehicle Inventory Input

A fair definition of vehicle types on the basis of their size and function for the purpose of defining their performance. This approach allows the definition of up to 10 types. The user can specify the vehicle age, mileage, vehicle maker, etc.

Vehicle Maintenance/Downtime Input

Maintenance/downtime information is used for long- or short-term analysis. For each vehicle, Maintenance/downtime data is an essential element in deciding which maintenance alternative applies to a particular vehicle type.

The software developed for TAMS implements the following steps:

1. Calculates the probabilities for each vehicle conditions.
2. Calculates the expectation value.
3. Finally, it takes the square root of the calculated integral.

The software was developed in ACCESS for the PC environment, in order to make use of the subroutines available to all modules. The subroutines were built in Dynamic Link library.

APPENDIX B

Life Cycle Cost Model

Life Cycle Cost Analysis

In 1998, Federal Highway Administration (FHWA) established the Office of Asset Management. It works closely with the American Association of State Highway and Transportation Officials (AASHTO) to provide technical assistance to help state transportation agencies to implement the Asset Management System (AMS) nationwide.

Since the physical assets are deteriorating day by day, to ensure high-quality service while facing limited staff resources, state and local agencies turned to AMS to find cost-effective solutions. In June 1999, the Governmental Accounting Standards Board (GASB) issued statement No. 34, “Basic Financial Statements for State and Local Governments,” which requires state and local governments to enhance the information provided as part of their annual financial statements. This new approach covers all capital assets and long-term liabilities and recommends government agencies establish transportation infrastructure values in reporting capital assets as part of their financial statements. The GASB 34 also pushes the state and local agencies to create and use AMS.

The Interim Final Rule (IFR) on Management and Monitoring Systems issued jointly by the FTA and FHWA, states that a Public Transit Management System (PTMS) is “a systematic process that collects and analyzes information on the condition and cost of transit assets on a continual basis. It identifies needs as inputs to the metropolitan and statewide planning process, enabling decision-makers to select cost-effective strategies for providing and maintaining assets in a serviceable condition.” Its major function is as an informational tool for making investment decisions about the existing transit assets. Asset management, as defined by Office of Asset Management, Federal Highway Administration, is a business process and a decision-making framework that covers an extended time horizon, which draws from economics as well as engineering, and considers a broad range of assets [1].

Traditionally, rural and small urban transit agencies have approached the maintenance and operation of transit systems with a crisis-based approach due to shortage of financial support, maintenance staff, and maintenance equipment. As a result, the impact of important considerations such as operation duration and service quality, life cycle costs, environmental impacts, safety requirements, etc. are not fully explored. State and local transit agencies are frequently faced with budget shortage problems. Due to limited budget and financial support, fleet managers turned to management systems to achieve high returns on the constrained investment. However, there are several problems in development of an efficient and effective management system. They include multiple, often conflicting objectives, uncertainties to asset future conditions and uncertainties related to future decisions, and a lack of qualitative and quantitative data.

A systematic approach for the determination of deterioration of transit asset and an integrated transit asset management system are necessary to fully understand the complete status of this transit asset system. A well-designed integrated Transit Asset Management System (TAMS) should include transit asset condition assessments, a well-defined condition rating system, updateable prediction models for asset performance, life cycle analysis, and development of prioritization schemes for selecting maintenance/repair options. A rural and small urban Transit

Asset Management System (RSUTAMS) can play a key role to monitors and optimizes the preservation, upgrading and timely maintenance of the transit system, and more specifically, the vehicles and other fixed assets, through cost-effective management, programming, and resource allocation decisions. It's a decision support tool developed to assist Kansas state and local transit agencies in determining how and when to make investments on vehicle and other fixed assets to maintain or improve the existing asset, identify current and future deficiencies, estimate the backlog of investment requirements, and predict future requirements of the upcoming fiscal year.

A RSUTAMS serves as one of the principal means by which the transit agencies can develop innovative near-term or long-term solutions to meet mobility, environmental, and energy objectives placed on it. Because it uses optimization techniques to obtain minimum costs of maintenance/repair strategies over the life cycle of transit system, the 'what-if' analysis in this system will help the fleet managers to make the best cost-effective decisions about maintenance of vehicles (whether to repair, overhaul, or replace) to make full use of each dollar and get adequate funding. By taking into account future conditions as a consequence of present maintenance/repair actions, the best action alternative and its priority and schedule can be determined.

Many transit agencies are using the life cycle cost analysis (LCCA) method to help them choose the most cost-effective transit asset maintenance and replacement alternatives for long term planning. LCCA allows transit agencies to quantify the differential costs of alternative M/R options for a given vehicle or other asset since LCCA considers all agency expenditures, including capital cost, operation cost, and maintenance cost, throughout the life of an alternative. Using LCCA, transit agencies can design M/R alternative results in the lowest total cost over the life of a vehicle, analyze the M/R cost impacts of M/R alternative strategies, and determine the most economical replacement time.

Usually, M/R actions are cheaper than replacement of a vehicle, but M/R cannot go on forever. The economic analysis using LCCA should be conducted for building a life cycle profile in terms of annual total cost. The profile represents the relationship of the combined cost and the amount of time it lasted, which, in general, is a U-shaped curve with a single minimum point. Usually, the single minimum point is called an economic life point and the age of the vehicle at the minimum cost point is known as the economic life of the vehicle.

The basic LCCA steps are as follows:

1. Identify long-term potential M/R alternative strategies including the current M/R activities, and the planned future M/R activities
2. Determine M/R activity timing and then design schedule of these activities
3. Estimate the cost of these activities
4. Calculate total life cycle cost of a vehicle including detailed purchase cost, operation cost, and maintenance cost
5. Find the point of the economic life of a vehicle, which is the best time for replacement. Costs due to vehicle maintenance schemes may be expressed in monetary terms (e.g., vehicle maintenance and operating costs, savings in reducing road call times)

Since the M/R activities will span several years, LCCA can apply different discounting methods, such as the net present value, internal rate of return, or benefit-cost ratio, to convert all the costs to present value for alternative comparison. For each maintenance option to be compared, the net costs (or benefits) of implementing one option relative to the base option is calculated year by year.

The life cycle cost of a vehicle can be further divided for detailed calculation purposes. The capital cost consists of purchase price or replacement cost and depreciation. The maintenance cost consist of maintenance parts and labor cost, vehicle downtime, or road calls. The cost of operation includes logistics required to operate the vehicle and to keep it in operation during its useful life. Although the capital cost is likely high, the capital cost would increase with the increasing reliability and the support costs decrease as reliability increases because the frequency of maintenance declines. On the other hand, as a vehicle grows older, the change in the amortized cost decreases while its operating and maintenance costs typically increase. Eventually, the sum of the two costs reaches a minimum and then starts to increase. Therefore, these two costs should be combined to analyze in order to determine the point at which the vehicle should be retired or replaced.

LCCA take into account future maintenance costs associated with each action alternative and ensures selection of the best economic maintenance strategy and optimal action time. The basic equation is shown as follows:

$$LCC = C + \Sigma\,(M + D + R)(1+i)^{N},$$

where

N = number of years
Y = life of a vehicle
LCC = total life cycle cost at N year
C = total capital cost
M = maintenance/repair cost at year N
D = depreciation
R = road call cost at year N

To apply the LCCA model, one needs a lot historical data collected over several years. The data collected from the transit agencies were not enough to conduct the LCCA. One also needs maintenance and operation data for at least 10 years because the current FTA minimum life of a standard bus is 12 years. However, to explain the LCCA method implemented in RSUTAMS, a hypothetical example is used to go through the LCCA procedure. As an example, a vehicle with an initial purchase price of 300,000 dollars is used.

Depreciation cost is the cost due to the reduction in actual value of a vehicle because of usage and age. Buses are purchased for the task of passenger transportation, a task which is associated with a certain lifetime. The service output method is used to calculate the depreciation cost. The depreciation is calculated by the Sum-of-the-Years' Digits Method. The digits from 1 to n year standard lifetime inclusive are summed. The total, T can be calculated from the following:

$$T = \tfrac{1}{2}\, n(n+1)$$

Therefore, the depreciation in year i can be calculated from following equation. Notice that the depreciation in year I, Di, decreases by a constant amount each year:

$$Di = (\text{Purchase Price}–\text{Expected Salvage Value})(\text{Standard Lifetime Years}–i+1) / T$$

If a standard bus's life is 12 years and average usage mileage is 20,000 miles, the Expected Salvage Value at end of standard lifetime equal to 0 dollars. Usually, vehicle maintenance/repair costs increase rather evenly and are expected to increase with age. However, the costs for an individual vehicle may vary greatly. This is a result of major overhauls or repairs such as engine rebuilding and transmission replacement, which cause unusually high costs in a year. If a certain PM scheme was selected for a vehicle, the maintenance/repair costs may be predictable. Transit agencies need to keep annual cost records on an individual vehicle basis.

As the mileage increases and the vehicle ages, the cost of lost time due to vehicle breakdowns on the road also increases. Since it is difficult to estimate the costs of road calls and downtime in money value, some indirect estimation methods of downtime costs are developed. Ray has proposed that the total annual cost of downtime may be estimated as the cost of maintaining second-line equipment if second line units are provided to reduce the effect of downtime. However, for a small transit agency, it is not practical to use this method. USDOT has suggested in Equipment Management System that downtime costs may be stated simply as the additional costs required for renting an additional vehicle to cover downtime. Using this concept, downtime costs can be calculated as follows:

$$\text{Annual Downtime Costs} = \text{Annual Downtime Hours X Rental Rate Per Hour}$$

Notice that downtime costs may increase greatly and become significant part of the total life cycle cost as a vehicle ages. In addition to using total annual cost, the annual life cycle cost per mile is used in LCCA to consider the effect of vehicle mileage usage, namely, when buses get older, the yearly mileage decreases. Calculating all the costs in the LCCA is explained above and the results are shown in Table A.1. The actual life cycle cost curve can be generated for each vehicle based upon the calculated costs.

LCCA can help transit agencies make two major decisions; selecting an optimal PM long-term plan and then estimating the best replacement timing. As shown in the example, the lowest cost or smallest annual life cycle cost at year 10 is the best timing for replacement.

Table 40. LCCA costs

Age (years)	Mileage (miles)	Depreciation ($)	PM ($)	CM / Downtime ($)	Total Cost ($)
1	36000	30769	2000	1000	33769
2	35000	28205	2200	1000	31405
3	35500	25641	2600	1500	29741
4	35000	23077	2300	2300	27677
5	34000	20513	2400	3000	25913
6	34000	17949	2800	5100	25849
7	33000	15385	2400	5800	23585
8	33000	12821	2500	7300	22621
9	33000	10256	2900	8800	21956
10	31000	7692	2500	11300	21492
11	31000	5128	2600	14100	21828
12	30000	2564	3000	16600	22164
13	30000	0	2600	20700	23300
14	30000	0	2700	20100	22800
15	28000	0	3000	19200	22200
16	28000	0	2700	21300	24000
17	27000	0	2700	21000	23700
18	26000	0	3000	20300	23300
19	25000	0	2700	24100	26800
20	25000	0	2800	25700	28500

APPENDIX C

Vehicle Classification Standards

Vehicle Classification Standards

The following vehicle classification standard used in the study can be found in *TCRP Report 61, Analyzing the Costs of Operating Small Transit Vehicles.*

Category 1—Van: Standard vans have front engines with rear-drive. Most vans have a separate body and frame, and they are built on a chassis intended for commercial use. To provide wheelchair accessibility, vans are equipped with a lift or ramp as well as a raised roof with a taller door unit that provides easier entry. With modifications for wheelchair access and securement, total passenger capacity—which includes one wheelchair position—is 10 to 11 passengers. The useful life of a van is projected at 4 years.

Category 2—Van Cutaway, Single Wheel: The chassis and partial cab are obtained from a truck manufacturer and a specialist body builder places a bus body on the chassis, integrating the bus body with the front of the cab, retaining the short hood. With a single wheel in the rear, these vehicles are somewhat lighter and shorter than cutaways described in Category 3. These vehicles have a total passenger capacity of 13. Useful life is considered 4 years.

Category 3G—Van Cutaway, Dual Wheel, Gasoline: Vehicles in this class are similar to those in Category 2; however, there are two wheels on the rear axle. This allows models with longer lengths, which also result in heavier vehicle weights. Total passenger capacity, including ADA-mandated wheelchair positions, is assumed to be 18. While the useful life of vehicles in this category ranges from 4 to 5 years, the model considers the useful life to be 5 years. Vehicles in this category are fueled with gasoline.

Category 3D—Van Cutaway, Dual Wheel, Diesel: These vehicles have basically the same appearance and passenger capacity as those in Category 3G above; however, they are diesel fueled rather than gasoline. Use of diesel affects both maintenance and operations. Again, while the useful life of vehicles in this category ranges from 4 to 5 years, the model considers the useful life to be 5 years.

Category 4—Purpose Built, Front Engine: Vehicles in this category are purpose built, medium-duty. Models within this category vary in price, length, and weight. Total passenger capacity is 22. The useful life of vehicles within this category ranges from 5 to 7 years. The model has assumed a useful life of 6 years.

Category 5—Purpose Built, Rear Engine: These vehicles are similar to those in Category 4; however, they have engines in the back of the bus. Useful life is considered to be 7 years in the model.

Category 6—Medium-Duty, Low-Floor Front Engine: Vehicles in this category are purpose built, medium-duty with a lowered floor to improve accessibility for passengers. In this category, engines are in the front. Total passenger capacity is assumed to be 20. The useful life is 7 years.

Category 7—Heavy-Duty, Low-Floor Front Engine: These are purpose built, heavy-duty, low-floor vehicles, with engines in the front. A major difference with vehicles in this category is life expectancy; the heavy-duty vehicles of Category 7 have a useful life of 12 years.

Category 8—30-Ft, Heavy-Duty Bus: Vehicles in this class are essentially shorter versions of traditional 40-ft transit buses, with a useful life of 12 years. Recently, more 30-ft low-floor buses are coming on the market, but no actual operating data were available to evaluate the low-floor version of the 30-ft bus.

APPENDIX D

Data Collection and Adjustments

Data Collection and Adjustments

Figure D1 provides a copy of the "Survey Forms of Transit Asset Management System" used in the study. Data collected from Oats, Inc., have 63 data points as shown in Table D1. Eleven data points of January 2001 have been taken out for OP model prediction accuracy evaluation purpose. The rest forms the Adjusted Data Set presented in Table D2. The outliers indicated in Table D1 were taken out and the data left mixed with extrapolated data points are referred to as Refined Data Set presented throughout this report.

Vehicle ID VIN or License or Number	Date of Service	Purchase Price	Vehicle Classification Type	Current Condition *State (0 - 4) on the Date*	Mileage	Age (Month)	% Of Paved Road	Maximum Passenger Capacity	Passenger Volume
70	Jan-00		MINI-VAN	4	8445	6		7	
	Jan-01			3	20601	18		7	

Entire Maintenance History

Vehicle ID VIN or License or NO	Date of Service	Preventive Maintenance Expense	Corrective Maintenance Expense						
			Engine Related	Cooling System	Transmission Related	Electrical System	Brake Related	Body Improvement	Other Costs
70	Jan-00								
	Jan-01	49.00							

Vehicle ID VIN or License or NO	Date of Service	Notes	Total Maintenance Costs
70	Jan-00		0.00
	Jan-01		49.00

Figure D1. Survey forms of transit asset management system

Table D1. Field data from Oats, Inc., of vehicles in category 2 (63 data points)

Indicator	Vehicle ID	Inspection Time	C.S.	Age	Mileage	PM	C.M.	Mcost
	387	Jan-88	4	7	8066		0.00	0.00
		Jan-89	2	19	36198	23.79	92.91	116.70
		Jan-90	2	31	61776	18.50	400.65	419.15
		Jan-91	2	43	88037	2.38	0.00	2.38
		Jan-92	1	55	111996	7.50	120.00	127.50
		Jan-93	1	67	131947		148.70	148.70
		Jan-94	1	79	147026		172.72	172.72
		Jan-95	2	91	151800		0.00	0.00
		Jan-96	1	103	159980		153.07	153.07
Outlier		Jan-97	2	115	166612		0.00	0.00
Outlier		Jan-98	2	127	172053		0.00	0.00
Outlier		Jan-99	2	139	187845		0.00	0.00
Outlier		Jan-00	2	151	192485		0.00	0.00
TakenOut		Jan-01	2	163	198210		0.00	0.00
	608	Jan-94	4	5	12379		0.00	0.00
		Jan-95	4	17	49230		0.00	0.00
		Jan-96	3	29	86214	56.75	0.00	56.75
		Jan-97	2	41	121900	3.60	0.00	3.60
		Jan-98	2	53	155841	109.00	10.88	119.88
		Jan-99	1	65	187811	192.03	728.25	920.28
		Jan-00	1	77	204062		183.00	183.00
TakenOut		Jan-01	1	89	216531		0.00	0.00
	697	Jan-96	4	0	450		0.00	0.00
		Jan-97	4	12	44764	9.98	515.00	524.98
		Jan-98	3	24	66824	30.50	0.00	30.50
		Jan-99	3	36	91534	30.50	194.50	225.00
Outlier		Jan-00	2	48	114815	498.94	0.00	498.94
TakenOut		Jan-01	2	60	138676		437.75	437.75
	731	Jan-97	4	1	10499		0.00	0.00
		Jan-98	3	13	46378	44.00	35.00	79.00
		Jan-99	2	25	84170	228.31	0.00	228.31
		Jan-00	2	37	99116		355.50	355.50
TakenOut		Jan-01	2	49	114020		0.00	0.00
	737	Jan-97	4	3	8955	13.22	0.00	13.22
		Jan-98	3	15	43652		0.00	0.00
		Jan-99	3	27	75286	50.40	100.00	150.40
		Jan-00	2	39	111811		0.00	0.00
TakenOut		Jan-01	2	51	144438		0.00	0.00
	784	Jan-98	4	1	3903		24.75	24.75
		Jan-99	3	13	42786	225.51	258.00	483.51
		Jan-00	3	25	67944	40.00	171.44	211.44
TakenOut		Jan-01	3	37	932.4	259.00	0.00	259.00
	787	Jan-99	4	10	27003	27.46	6.50	33.96
		Jan-00	3	22	48689		0.00	0.00
TakenOut		Jan-01	3	34	100795		0.00	0.00
	790	Jan-99	4	9	47471	40.00	8.00	48.00
		Jan-00	3	21	90545	400.15	0.00	400.15
TakenOut		Jan-01	3	33	134408	75.00	278.00	353.00
	885	Jan-99	4	1	1851		0.00	0.00
		Jan-00	4	13	15936		0.00	0.00
TakenOut		Jan-01	3	25			0.00	0.00
	886	Jan-99	4	1	5338	40.00	0.00	40.00
		Jan-00	4	13	44720	95.00	0.00	95.00
TakenOut		Jan-01	3	25	71302	40.00	0.00	40.00
	887	Jan-99	4	1	4679		0.00	0.00
		Jan-00	4	13	34947		91.56	91.56
		Jan-01	3	25	65739		0.00	0.00
	895	Jan-00	3	10	62604	315.00	0.00	315.00
		Jan-01	3	22	132925	75.00	485.11	560.11
	973	Jan-00	4	2	6098	40.00	0.00	40.00
		Jan-01	3	14	63446	648.00	0.00	648.00
	1014	Jan-01	4	0	0		0.00	0.00
	1020	Jan-01	4	1	4443		0.00	0.00

Table D2. Adjusted data set (52 data points)

Indicator	Vehicle ID	Inspection Time	C.S.	Age	Mileage	PM	C.M.	Mcost
	387	Jan-88	4	7	8066		0.00	0.00
		Jan-89	2	19	36198	23.79	92.91	116.70
		Jan-90	2	31	61776	18.50	400.65	419.15
		Jan-91	2	43	88037	2.38	0.00	2.38
		Jan-92	1	55	111996	7.50	120.00	127.50
		Jan-93	1	67	131947		148.70	148.70
		Jan-94	1	79	147026		172.72	172.72
		Jan-95	2	91	151800		0.00	0.00
		Jan-96	1	103	159980		153.07	153.07
Outlier		Jan-97	2	115	166612		0.00	0.00
Outlier		Jan-98	2	127	172053		0.00	0.00
Outlier		Jan-99	2	139	187845		0.00	0.00
Outlier		Jan-00	2	151	192485		0.00	0.00
	608	Jan-94	4	5	12379		0.00	0.00
		Jan-95	4	17	49230		0.00	0.00
		Jan-96	3	29	86214	56.75	0.00	56.75
		Jan-97	2	41	121900	3.60	0.00	3.60
		Jan-98	2	53	155841	109.00	10.88	119.88
		Jan-99	1	65	187811	192.03	728.25	920.28
		Jan-00	1	77	204062		183.00	183.00
	697	Jan-96	4	0	450		0.00	0.00
		Jan-97	4	12	44764	9.98	515.00	524.98
		Jan-98	3	24	66824	30.50	0.00	30.50
		Jan-99	3	36	91534	30.50	194.50	225.00
Outlier		Jan-00	2	48	114815	498.94	0.00	498.94
	731	Jan-97	4	1	10499		0.00	0.00
		Jan-98	3	13	46378	44.00	35.00	79.00
		Jan-99	2	25	84170	228.31	0.00	228.31
		Jan-00	2	37	99116		355.50	355.50
	737	Jan-97	4	3	8955	13.22	0.00	13.22
		Jan-98	3	15	43652		0.00	0.00
		Jan-99	3	27	75286	50.40	100.00	150.40
		Jan-00	2	39	111811		0.00	0.00
	784	Jan-98	4	1	3903		24.75	24.75
		Jan-99	3	13	42786	225.51	258.00	483.51
		Jan-00	3	25	67944	40.00	171.44	211.44
	787	Jan-99	4	10	27003	27.46	6.50	33.96
		Jan-00	3	22	48689		0.00	0.00
	790	Jan-99	4	9	47471	40.00	8.00	48.00
		Jan-00	3	21	90545	400.15	0.00	400.15
	885	Jan-99	4	1	1851		0.00	0.00
		Jan-00	4	13	15936		0.00	0.00
	886	Jan-99	4	1	5338	40.00	0.00	40.00
		Jan-00	4	13	44720	95.00	0.00	95.00
	887	Jan-99	4	1	4679		0.00	0.00
		Jan-00	4	13	34947		91.56	91.56
	895	Jan-00	3	10	62604	315.00	0.00	315.00
		Jan-01	3	22	132925	75.00	485.11	560.11
	973	Jan-00	4	2	6098	40.00	0.00	40.00
		Jan-01	3	14	63446	648.00	0.00	648.00
	1014	Jan-01	4	0	0		0.00	0.00
	1020	Jan-01	4	1	4443		0.00	0.00