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Applying Two Statistical Models to Condition-Based Machinery Inspection and Maintenance - Railroad Car Truck Case

by

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ABSTRACT

Freight cars are an important and integral part of the railroad system of the United States and Canada. These cars are equipped with a component, known as "truck", which act as an interface between the car body and the truck, and as a suspension system. A high level of expense is incurred on truck maintenance. In particular, two significant costs may be incurred due to the difficulty in knowing the true truck condition, especially the internal truck condition.

The research presented by this thesis attempts to address the problem by applying two statistical forecasting techniques, discrete choice method and performance threshold method, to develop a more cost-effective inspection approach. The techniques presented were also applied to a case study.

In terms of underlying behavioral theory, the performance threshold method is considered stronger than discrete choice method. From a computational point of view, performance threshold and discrete choice methods are acceptable in that well-written computer software is available for implementation. The results from the case study show that the performance threshold models are better than the other models in terms of the quality of estimation and prediction.

Further work may be done along the directions of providing better data and conducting more insightful modeling.

Thesis Supervisor: Dr. Patrick Little.
Title: Research Associate, Department of Civil and Environmental Engineering.

To my parents who brought me to the world and
my grandmother who fed me to be a man.

Acknowlegement

This thesis marks the end of a life-long-reaching period of time, two years of studying in the Master of Science in Transportaion program at MIT, albeit there were and will be other events of the same importance in my life.

I would first acknowledge the Center for Transportation Studies at MIT for their bringing me into the wonderful institute and supporting my study through the years. Being an undergraduate student majoring in management science at Peking University which does not have any engineering discipline at all, I have grown to be more broadly competent both professionally and personally in the unique environment at MIT.

Dr. Patrick Little, my thesis supervisor, who is an active practitioner and researcher in rail transportation area, deserves many thanks from me. His diligence, intelligence and kindness have been always encouraging me to work. His advice and direction were very helpful and insightful.

Professor Moshe Ben-Akiva responded to all my questions almost in real-time although he was very busy. Mr. Carl Martland gave me many important directions for the thesis.

I am very glad to be one of the 5-008'ers during the two years and I owe a special debt to Adriana Bernardino, Amalia Polydoropoulou, John Bowman, Jai-Kue Park, Kalidas Ashok and Dinesh Gopinath, who treated me as a younger brother and gave me a lot of help, ideas and encouragement.

Many other names should be mentioned here, Marty Schlenker, John Wilson, Jeffrey Sriver, Nicola Shaw, Hong Jin, Andras Farkas, Yan Dong, Yoshiyasu Murashige ....

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Chapter 1

INTRODUCTION

1.1. Problem Statement

Freight cars are an important and integral part of the railroad system of the United States and Canada. To enable the movement of the cars, they are equipped with a suspension system known as freight car trucks. It is not surprising that large amounts of money are spent to keep these cars in working order, and a high level of expense is incurred on car truck maintenance.

It will be shown that under the current car truck inspection and maintenance policy, some cost is incurred because of the difficulty of knowing the true condition of the car truck, especially the condition of truck internal parts which are located under the car bodies and hence unable to be inspected without taking the car bodies off. Typically, this happens in two situations. One situation is the overestimation of the condition of wear of internal parts, and the other is the underestimation.

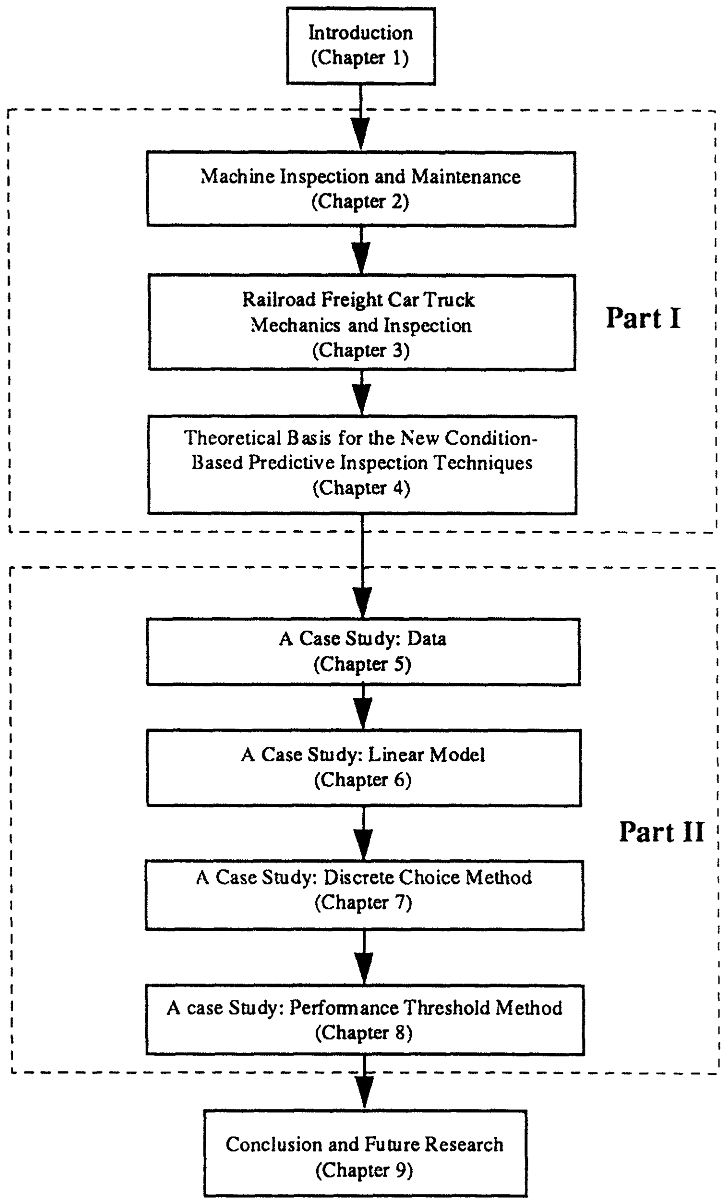
The research presented by this thesis attempts to address the above problem by applying two statistical forecasting techniques, discrete choice method and performance threshold method, to develop a more effective inspection aproach.

1.2. Structure of the Thesis

This thesis is organized in terms of the disciplines applied and can be illustrated by the flow chart shown in Figure 1.1. With a chapter of introduction at the beginning of the thesis and one of conclusions and future direction by the end, the main body of the thesis consists of two parts. The first part contains chapters 2, 3 and 4, each focused on one of the three areas of knowledge preparatory for the second part. Chapter 2 introduces the general framework of machine maintenance and inspection. Maintenance is shown to consist of two major categories: unplanned and planned maintenance. These two categories are in turn divided into several types - corrective maintenance under the unplanned category, and scheduled preventive maintenance and condition-based predictive maintenance under the planned category. Chapter 3 introduces the train-track system and the mechanics, inspection and maintenance of three-piece freight car trucks. Chapter 4 introduces the theoretical basis for the proposed condition-based predictive inspection techniques - discrete choice method and performance threshold method. For the discrete choice method, this is done by presenting the basic theory in its traditional contexts - freight mode choice, and then extending analogously to the freight car truck case. For the performance threshold method, the basic theory, followed by a simple example, is presented directly in the freight car truck inspection context.

The second part of the thesis, including chapters 5, 6, 7 and 8 is a case study of employing the proposed predictive techniques to freight car truck inspection and maintenance. Chapter 5 describes the data for the case study. Chapters 6, 7 and 8 present the application of a linear model, discrete choice models and performance threshold models in the case study.

Figure 1.1. The Structure of the Thesis



1.3. Contribution of the Research

The research of this thesis makes contributions to the state of knowledge of transportation vehicle maintenance. Primarily, this research demonstrates that two statistical techniques used in other areas may be effectively applied to assess the condition of a machine. A practical contribution which follows from this is the application of these techniques to freight car truck inspection and prediction. This has the potential to generate very large cost savings for freight car owners.

Chapter 2

MACHINE INSPECTION AND MAINTENANCE

This chapter provides a review of machine maintenance methods. The definition and the framework of maintenance is presented first. This is followed by the introduction to the two categories of maintenance: planned and unplanned maintenance. Finally, condition-based predictive maintenance for complex machinery is presented.

2.1. Maintenance

This section presents the definition of maintenance first. Then various type of maintenance methods are presented which leads to the framework of maintenance methodologies.

Maintenance has been defined as (BS 3811: 1984):

> *The combination of all technical and associated administrative actions intended to retain an item in, or restore it to, a state in which it can perform its required function. This required function may be defined as a stated condition.*

The key words to notice in this definition identify the fact that there are both technical and administrative actions involved in maintaining an item of equipment in a satisfactory and functional state. Therefore maintenance actions can be split into two distinct categories, that is those without a logical and predetermined administrative plan, and those organized with forethought to produce a logical and predetermined administrative plan of action. These two categories are named **unplanned** and **planned maintenance**, respectively.

Unplanned maintenance is the strategy often known more colloquially as "run to failure" or "do nothing until it breaks". In effect, unplanned maintenance is a repair strategy. The major unplanned maintenance is corrective maintenance.

Planned maintenance primarily includes two types: scheduled preventive maintenance and condition-based predictive maintenance. Scheduled preventive maintenance is the strategy under which maintenance is done at predetermined time or usage intervals identified on an historical basis of operation and failure. Condition-based predictive maintenance is the strategy that maintenance is done as the result of some prediction of the operational effectiveness or efficiency based on the condition of the machine. Many techniques can be used to monitor the condition, such as visual, performance, vibration and wear monitoring. Figure 2.1 illustrates the framework of machine maintenance presented above.

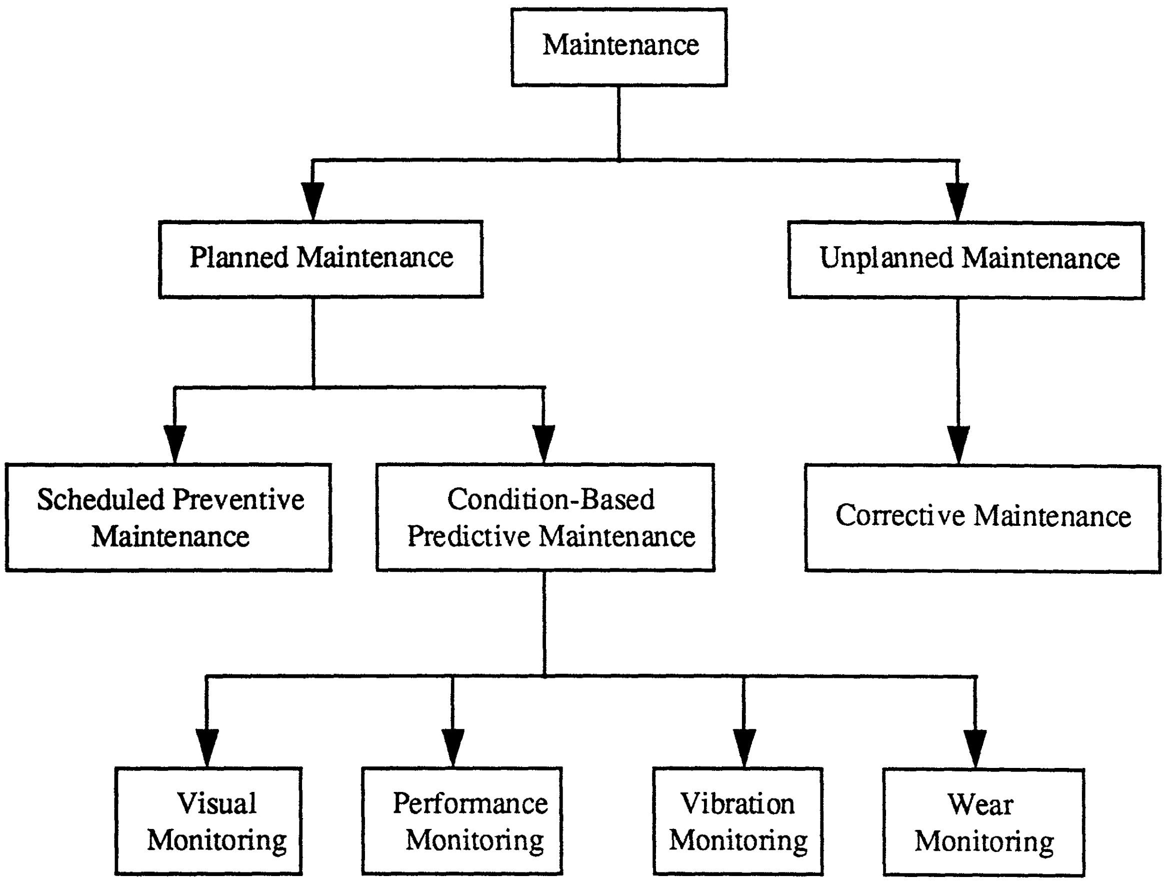
2.2. Unplanned Maintenance

Unplanned maintenance may be formally defined as follows (BS 3811 : 1984):

Maintenance carried out without a predetermined plan.

Put informally, the equipment continues in operation until it fails, at which point it is either repaired or replaced (Davies, 1990).

Figure 2.1. The Framework of Maintenance



Source: *Condition-based Maintenance and Machine Diagnostics*, J.H. Williams, A. Davies and P.R. Drake, 1994.

The primary policy under this strategy is corrective maintenance. Corrective maintenance is carried out after a failure has occurred and is intended to restore an item to a state in which it can perform its required function.

Unplanned maintenance is therefore suitable only in either (or both) of two circumstances: unpredictable failure events, or low costs when failures occur. Where components fail randomly and provide no prior indication of impending failure, this type of maintenance remains the only option. Also, where unscheduled stoppages cause minimal inconvenience, this type of maintenance may well be a low cost option. In general, unpredicted failures can be reduced by appropriate design and analysis of failure rates.

2.3. Planned Maintenance

Planned maintenance may be defined as follows (BS 3811 : 1984):

Maintenance organized and carried out with forethought, control and the use of records to a predetermined plan.

More specifically, planned maintenance is carried out at predetermined intervals or corresponding to prescribed criteria and intended to reduce the probability of failure or the performance degradation of an item.

Embodied in the above definition is the desire to in some way prolong the effective operation, availability or useful life of a system, or to avoid very high costs due to failures, by conducting the regular inspection of, and/or maintenance (repair) on, the equipment in question. Obviously the trick is to do so cost-effectively, given that the maintenance department is a non value adding division of the company, and usually has severely restricted resources, both in manpower and money.

Therefore, it is important to attempt to **optimize** planned maintenance in a cost-effective sense by identifying:

1. The appropriate **critical production machinery** on which it can be effectively used.

2. The most efficient method of determining the length of the time **interval** or **criterion** which dictates when the maintenance should be undertaken.

This last requirement results in the two major subdivisions of planned maintenance: scheduled preventive maintenance and condition-based predictive maintenance.

2.3.1. Scheduled Preventive Maintenance

This approach attempts to forestall the occurrence of breakdown by identifying on an historical basis, the duration of the failure interval exhibited by a component or machine. Accurate failure data in the form of maintenance records must therefore be available to establish typical component or machine failure patterns. An estimate can then be made of the relevant failure rate and appropriate maintenance interval. Thus the definition of scheduled preventive maintenance is (BS 3811 : 1984):

> *Maintenance carried out to a predetermined interval of time, number of operations, mileage etc.*

This approach has some inherent difficulties, mainly concerning the derivation of proven criteria whereby the predetermined time interval is established. Most maintenance activities are designed or planned around the entire system rather than the components or elements which make up the system. Barlow and Proschan (1965) have shown that the failure rate of a system of components tends to be exponentially distributed (i.e. appear random), even if the components are subject to increasing failure rates (i.e. predictable failure modes). This makes selecting an appropriate interval quite difficult. The difficulties / disadvantages are outlined below, and need to be carefully considered before the implementation of a scheduled maintenance scheme is undertaken.

1. In cases where the estimate of failure time is conservative, a risk exists that the system or component may be replaced under the scheduled maintenance regime well before its useful life has elapsed. This results in the conduct of excessive and unnecessary

maintenance, leading to the expensive overstocking of spare parts and the incurring of superfluous labor cost.

2. Conversely, if the estimate of failure time is too optimistic, a risk exists that the system or component may fail in service, with all that this implies for the attendant inconvenience and subsequent cost.
3. When estimating the failure time, due consideration should be given to any variation in the loading that a component or system may experience during its normal operation. Allowing for such variations can considerably complicate the analysis and the subsequent prediction of a probably failure time. This leads to wide variations in the accuracy of failure prediction and hence to the problems previously outlined.
4. As already stated, great care should be used when undertaking scheduled maintenance, for when applied to all but the most simple of systems, the stripping down and refurbishment of equipment can of itself induce further system failures.

2.3.2. Condition-Based Predictive Maintenance and Inspection

Condition-based predictive maintenance attempts to seek a way to determine the actual operating condition of a system or component at any point in time. It may defined as follows (BS 3811 : 1984):

> *Maintenance initiated as a result of the prediction based on the knowledge of the condition of an item from routine or continuous inspection.*

Or more informally as, components are periodically inspected by manual or automatic systems in order that their condition may be assessed and to identify their degradation rates. A decision is then taken regarding replacement and/or repair and this is based upon an analysis of the monitored data (Seddon, 1984).

This concept of undertaking maintenance only when it is required, and based on the actual condition of a system or component is obviously very attractive. Hence the ability to forecast failure is the key element for the condition-based predictive maintenance to be taken. The key components for the forecasting ability are effective condition inspection and proper understanding of the relationship between the condition inspected and the system's reliability. Clearly the ideal technique would be one in which the true condition of the equipment would be known at all times and which would provide an accurate prediction of any potential failure or problem. Since this thesis is basically focused on condition-based predictive inspection, more about condition inspection is introduced.

Formally, the condition inspection is defined as follows (BS 3811: 1984):

> *The continuous or periodic measurement and interpretation of data to indicate the condition of an item to determine the need for maintenance.*

In many cases, the condition inspection is normally carried out with the item in operation, in an operable state or removed but not subject to major stripdown. Informally, inspection is described as the assessment of the current condition of plant and equipment by the use of techniques which can range from sophisticated computer-driven instrumentation to human sensing, in order to predict failure and to economically perform maintenance only when a potential failure is identified and at a time convenient to the production schedule (Davies, 1990).

Consequently, condition inspection is the means by which condition-based maintenance can be carried out, utilizing as it does the various techniques available to monitor and identify the impending failure. The use of condition inspection thus ensures that all necessary maintenance actions can be undertaken at a time appropriate to the predicted failure, and therefore allows the maximization of equipment availability through the timely and systematic organization of maintenance. In essence therefore the implementation of condition inspection can be described as, the performance of periodic or continuous comparative measurement on parameters which are suspected of reflecting the condition of a component, sub-assembly or system with the object that on analysis, the measurements may indicate the item's current condition and the future trend of its possible deterioration (Davies, 1990).

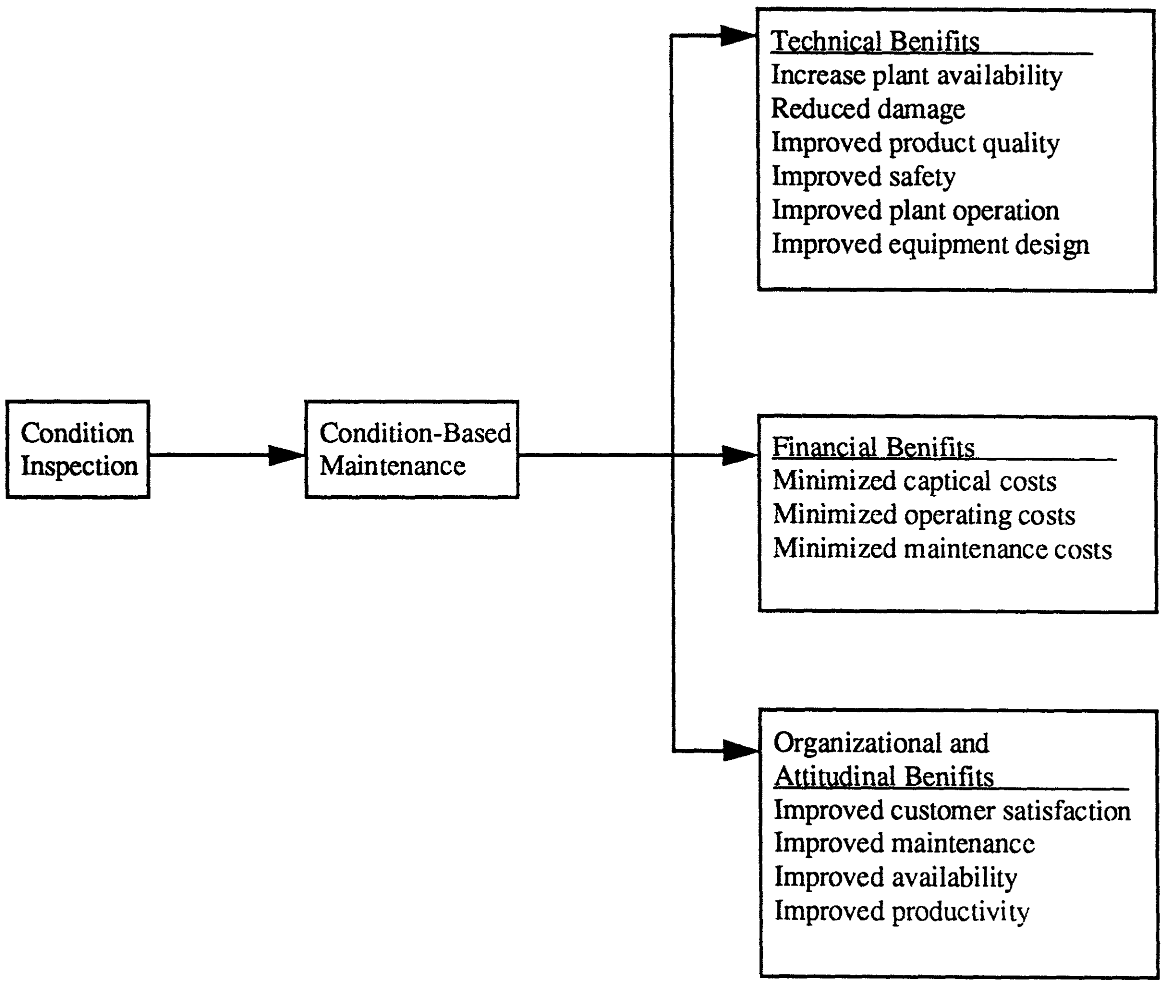
Thus through its contribution towards the planning of future maintenance action, condition inspection ensures that all decisions are made on substantive and corroborated diagnostic information, thereby providing a basis for cost-effective and logical decision making (Collocate, 1980). The integration of inspection techniques within the wider approach can yield many advantages, some of which are outlined in Figure 2.2. (Davies, 1990).

2.4. Condition-Based Predictive Inspection Technique for Complex Machines

A complex machine, or multi-component machine, consists of various components. As machine become larger and more complex, with an increasing number of parts to be maintained, the failures of the machine appear to exhibit an exponential nature with a constant rate and therefore negates the benefit of scheduled preventive maintenance. This is called Drenick's failure law (Drenick, 1968), which states that fthe reliability of a large series system of s-independent elements becomes exponential. Under this circumstance, condition-based predictive inspection and maintenance is more appropriate if the condition of machine, or of the key internal components can be predicted based on the condition of the easily inspected components of the machine, e.g. surface or peripheral parts. Maintenance is then performed only when the result from the prediction dictates.

Some techniques have been applied to the condition-based predictive inspection for complex machine. Discriminant analysis method was suggested by Park (Park, 1993) as one way to predict the machine's internal condition based on the external condition measurement of the machine which is easily observed.

Figure 2.2. Condition-Based Maintenance and Inspection



Source: *Condition-based Maintenance and Machine Diagnostics*, J.H. Williams, A. Davies and P.R. Drake, 1994.

By Bayes theorem and certain assumptions, the probability that the system characterized by the external variables (risk factors) $x_1, x_2, \cdots, x_k$ would develop a failure in a specified time period is given by

$$\Pr(1|x_1, x_2, \cdots, x_k) = \left[1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k)}\right]^{-1},$$

where $\xi = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k$ and is called the logit of risk factors.And, $\Pr(0|x_1, x_2, \cdots, x_k)$, the probability that the system characterized by the external variables (risk factors) $x_1, x_2, \cdots, x_k$ would in normal state in a specified time period, is simply equal to $1 - \Pr(1|x_1, x_2, \cdots, x_k)$.

Denote the penalty costs for **false-alarm** (the cost incurred in the situation that the internal condition is actually acceptable while it is predicted to be problematic) and **missing-failure** (the cost incurred in the situation that the internal condition is actually problematic while it is predicted to be acceptable) as C_a and C_f. Then, it is cost optimal to judge the system as follows:

The machine system is in failing state if $\Pr(1|x_1, x_2, \cdots, x_k) \cdot C_f > \Pr(0|x_1, x_2, \cdots, x_k) \cdot C_a$;

The machine system is in normal state if $\Pr(1|x_1, x_2, \cdots, x_k) \cdot C_f \le \Pr(0|x_1, x_2, \cdots, x_k) \cdot C_a$.

It is easily followed that the above rule can be further derived into

The machine system is in failing state if $\xi \cdot > C_f / C_a$;

The machine system is in normal state if $\xi \cdot \le C_f / C_a$.

The advantage of the discriminant method is that it can used to decide if the logit of "risk" of failure is great enough to judge whether to shutdown the system and repair. Some weaknesses of the method may also be mentioned. First, the quantity of the ratio of unconditional probabilities p_0 / p_1 is normally unknown for the reseacher and substituted by the sample approximation n_0 / n_1. It is obviously very easy for the sample share to be imfluenced by exogenous factors. Second, the standard normal distribution and equal covariance assumptions for the external variables are usually hard to meet in many real practices. Third, the method does not get to the "state-by-state" level of the machine, and just addresses the probability of failure (no failure) in next interval. But in many practices, it is very important to know the current operational condition of the machine system which can be at least practically categorize into several ordinal states. Fourth, there is no readily avaible good software to run the model and custom programs must be written to implement the estimation. This thesis proposes two other methods, discrete choice method and performance threshold method as alternative condition-based inspection techniques.

Chapter 3

Railroad Car Truck Inspection And Maintenance

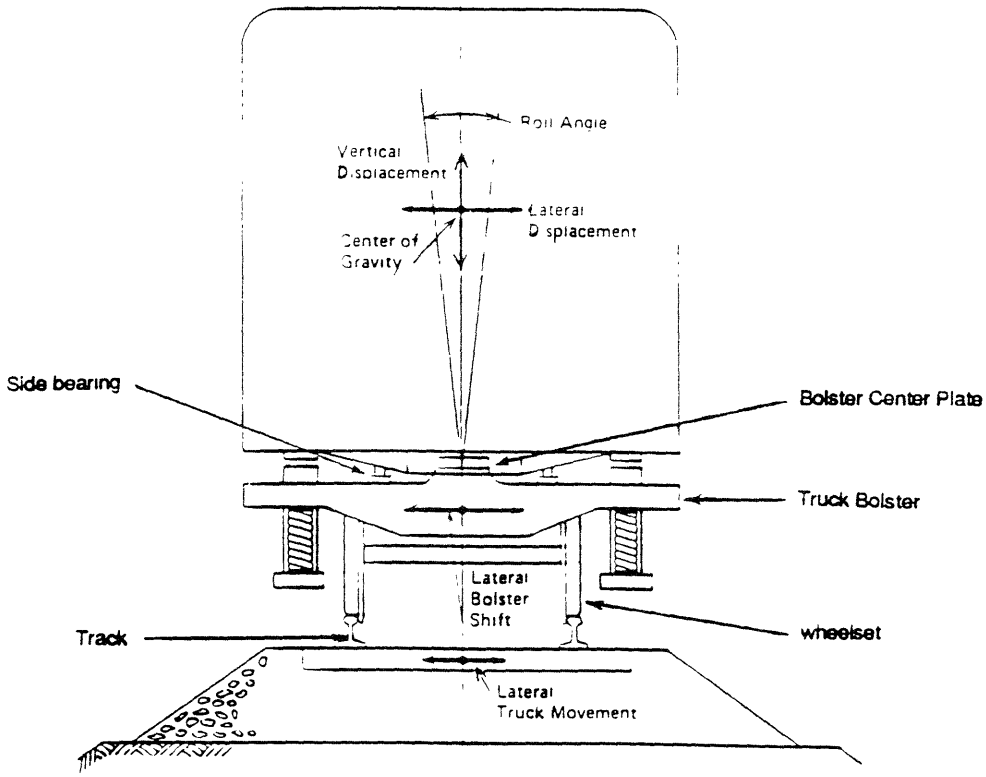
This chapter provides background knowledge of railroad car truck inspection and maintenance. A brief introduction to the train-track system, one of the major subjects of railroad engineering, is presented first. This is followed by a more detailed introduction to the three-piece freight car truck. Then the traditional inspection and maintenance policies for the freight car truck are presented, and this is followed by the problems associated with the traditional policies. At the end of the chapter, the idea of the new inspection policies is proposed.

3.1. Train-Track System

In some sense, the entire subject of railway engineering relates to the interaction between train and track. Train and track should be considered as a system with the track under load and train imposing that in a manner of mutual give and take (cf. Hay 1982).

In general, a train-track system is comprised of three parts, the car body, the truck (including wheelsets) and the track (figure 3.1). It should be mentioned here that

Figure 3.1. Train-Track System



Source: *Railroad Engineering*, W. Hay, 1982.

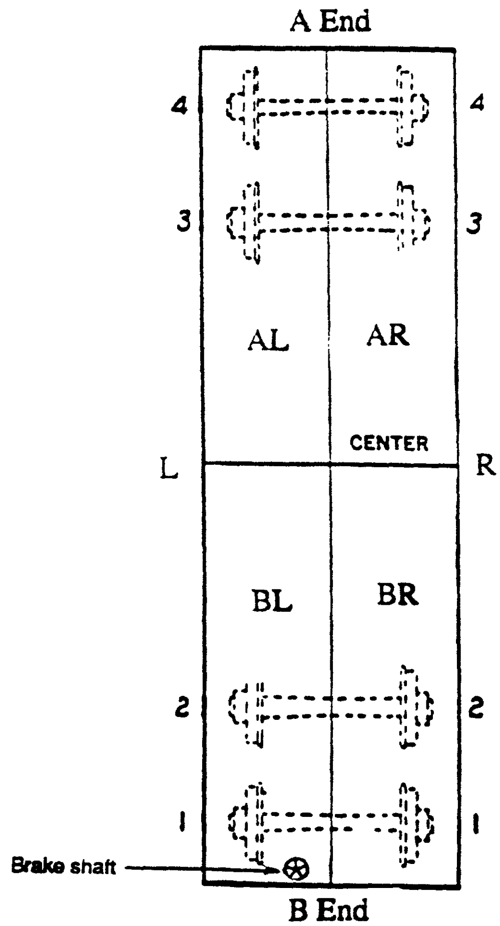
"car" refers to freight car through the entire thesis. The car body is supported on the truck bolsters through a center pin located in a center plate on the bolster. The truck consists primarily of three pieces: truck bolster, side frames and wheelsets. The wheels contact the rail which is in turn supported by ties and ballast. The car body is free to rock back and forth like a giant inverted pendulum as shown in figure 3.1. The amount of rock is limited by side bearing blocks with maximum clearance in the vertical position of a few inches. Therefore the car body is subject to vertical and lateral displacement. The truck is a major link between the train car body and the track. The interaction between the truck and the car body and the interaction between the truck (and wheels) and the track are both very critical to the proper performance of the whole train-track system. Since the research of this thesis is focused on the inspection and maintenance of the truck, more details about the truck and its interaction with the car body is discussed in section 3.3.

Before this, it is useful to mention the system governing the designation of location on a car where a part is located, damage occurred or repair is made. For a car equipped with four wheel trucks, the rule is as follows (AAR, 1992):

> *1. The end of a car upon which the brake shaft is located shall be known as B end and the opposite end shall be known as A end. If the car has two brake shafts, the owner shall have the respective ends, A and B, stenciled on car, on both sides, near each end.*
>
> *2. Facing the B end in their order on the right side, wheels, journal boxes, brake beams and other truck parts shall be known as R1, R2, R3 and R4. Similarly those on the left side shall be known as L1, L2. L3 and L4. The main structure of car is divided into four sections known as BR, BL, AR, and AL (figure 3.2.).*

This method of designating the locations is applied thoughout the thesis. For example, AR side frame implies the right side frame of the truck located at the A end of the car.

Figure 3.2. Designation of Location on a Car



Source: *Field Manual of the A.A.R. Interchange Rules*, 1992.

3.2. Three-Piece Freight Car Truck

In this section, the mechanics of the three-piece freight car truck are briefly presented. This is followed by the presentation of internal and external truck condition and measurements.

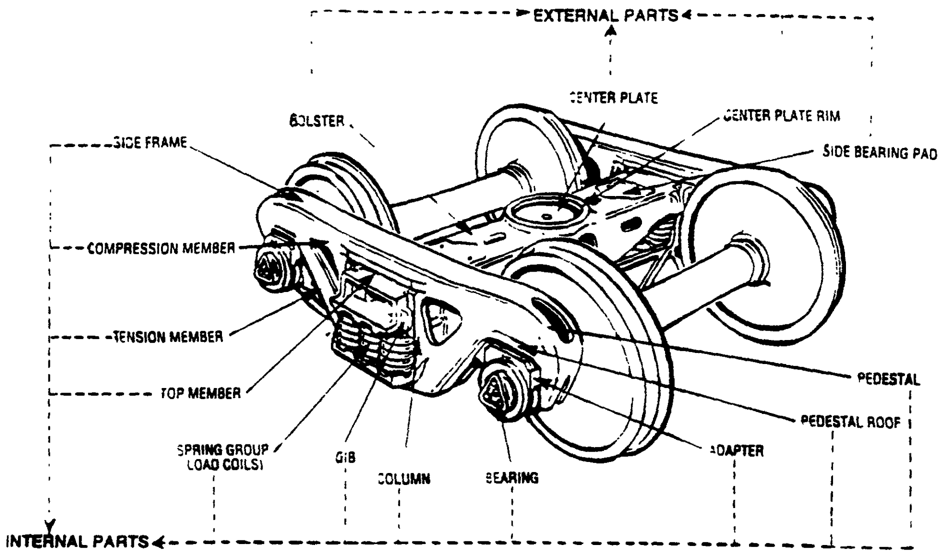
3.2.1. Overview of the Three-Piece Freight Car Truck

Freight car trucks provide the means for both support of the car body and the mobility of the freight car itself via steel wheels on steel rails. Four-wheel, three-piece swivel trucks are the standard for American railway passenger cars and conventional freight cars (cf. Freight Car and Caboose Trucks, 1980). A three piece-freight car truck is characterized by three types of parts: one truck bolster, two side frames and two wheelsets. Figures 3.3., 3.4. and 3.5. illustrate certain standard truck parts with specific description of the side frame and bolster areas.

When the train moves, shock, force and friction will happen to the car body and truck. To reduce the shock, a suspension system is designed and implemented for all types of car trucks. The system includes groups of springs carrying the load, a spring-loaded friction shoe, and in some case hydraulic shock absorbers. The friction shoe fits in the bolster friction pocket (figure 3.6. and 3.7.)

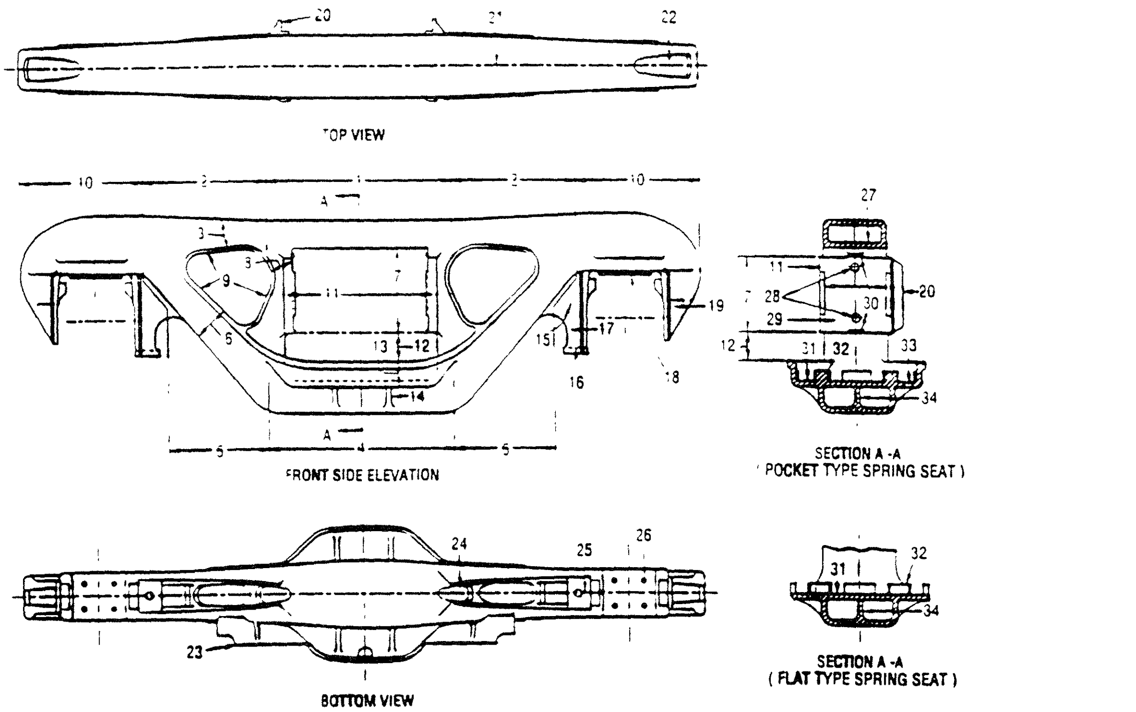
To dampen undesirable motions including vertical, lateral, longitudinal, rotational or any combination of such movements, several built-in mechanical friction liners, or plates, are designed and equipped on the freight car truck. For the purpose of consistency, "liner" instead of “plate” is used through the thesis. Three types of liners need to be mentioned here, i.e. column wear liner, pocket wear liner and roof pedestal liner. The column wear liner is located between the inner side wall of the column and the outer side of the friction shoe (figure 3.6. and 3.7.). When the bolster moves up and down, the outer side of the friction shoe wears with the column wear liner instead of the inner wall of the column. The pocket wear liner is the liner located between the bolster pocket slope and the friction shoe. The roof pedestal liner is

Figure 3.3. Three-piece Freight Car Truck



Source: *ASF Maintenance and Repair Manual, Super Service Ride Control and Ride Control Trucks*, 1994.

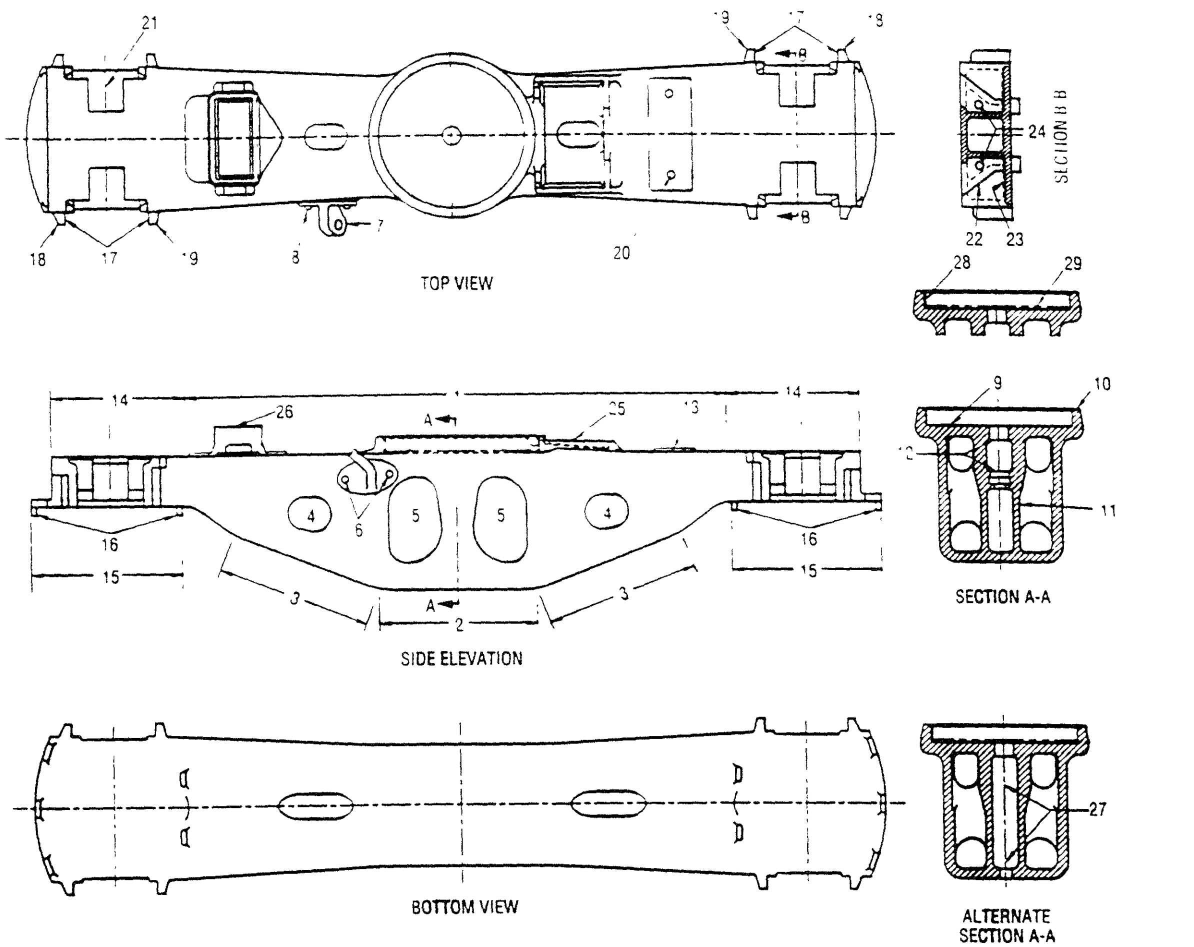
Figure 3.4. Side Frame



1. Top Member Center
2. Compression Members
3. Compression Member Flanges
4. Bottom Center
5. Diagonal Tension
6. Tension Member Flanges
7. Columns
8. Column Flanges
9. Windows
10. Top Ends
11. Inner Sides of Column
12. Lower Bolster Opening
13. Spring Seat Flanges
14. Spring Seat Ribs
15. Journal Bracket Flanges
16. Retainer Key Slot
17. Inner Pedestal Legs
18. Pedestal Roof Wear Liner
19. Outer Pedestal Legs
20. Bolster Anti-Rotation Lugs
21. Parting Line-Top Member
22. Top End Openings
23. Unit Brackets
24. Bottom Center Drain Holes
25. Parting Line-Bottom Member
26. Pedestal Roof Wear liner Bosses
27. Top Member Bridge
28. Wear Plate Retainer Holes
29. Column Face
30. Column Wear liner
31. Spring Seat
32. Spring Seat Bosses or Lugs
33. Spring Seat Drain Holes
34. Bottom Center Rib

Source: *ASF Maintenance and Repair Manual, Super Service Ride Control and Ride Control Trucks*, 1994.

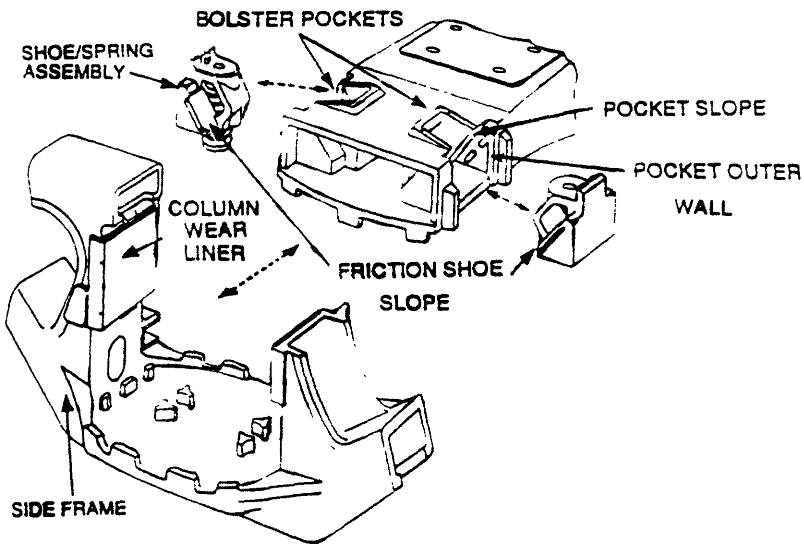
Figure 3.5. Bolster



1. Top or Compression Member
2. Bottom Center Member
3. Diagonal Tension Member
4. Side Wall Lightener Holes
5. Brake Rod Holes
6. Dead Lever Lug Retainer Holes
7. Dead Lever Lug
8. Dead Lever Lug Rivets or Bolts
9. Center Plate Inner Surface
10. Center Plate Rim
11. Center Post
12. King Pin Well
13. Side Bearing Pads
14. Ends
15. Spring Seats
16. Spring Seat Lugs
17. Columns
18. Outer Column Guides-Gibs
19. Inner Column Guides-Gibs
20. Side Bearing River or Bolt Holes
21. Friction Pockets
22. Friction Shoe Surface
23. Ride Control Spring Seats
24. Friction Shoe Retaining Pin Openings
25. C-Pep Pocket
26. Side Bearing Pocket
27. Locking Center Pin Opening
28. Center Plate Vertical Wear Liner
29. Center Plate Horizontal Wear Liner

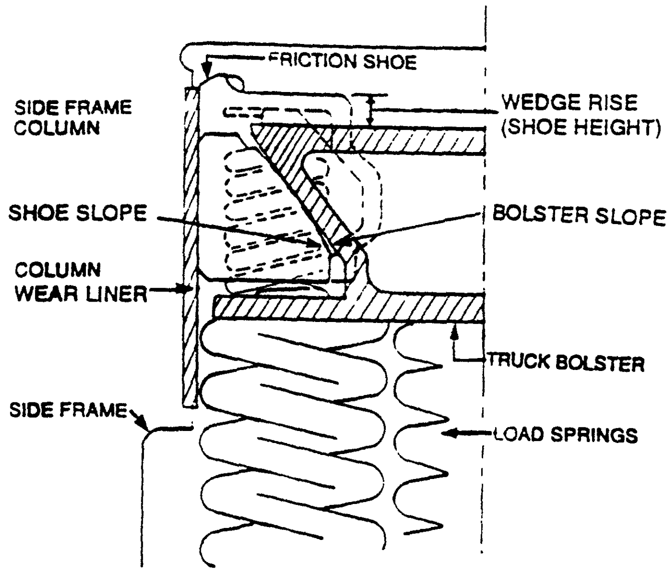
Source: *ASF Maintenance and Repair Manual, Super Service Ride Control and Ride Control Trucks*, 1994.

Figure 3.6. Suspension System



Source: *Technical Papers, 1990 ASME/IEEE Joint Railroad Conference.*

Figure 3.7. Wear Surfaces and Liners around Friction Shoe



Source: *Technical Papers, 1990 ASME/IEEE Joint Railroad Conference.*

the liner located between roof pedestal bearing adapter and truck sideframe. More detailed description about these two liners is given in the following chapters.

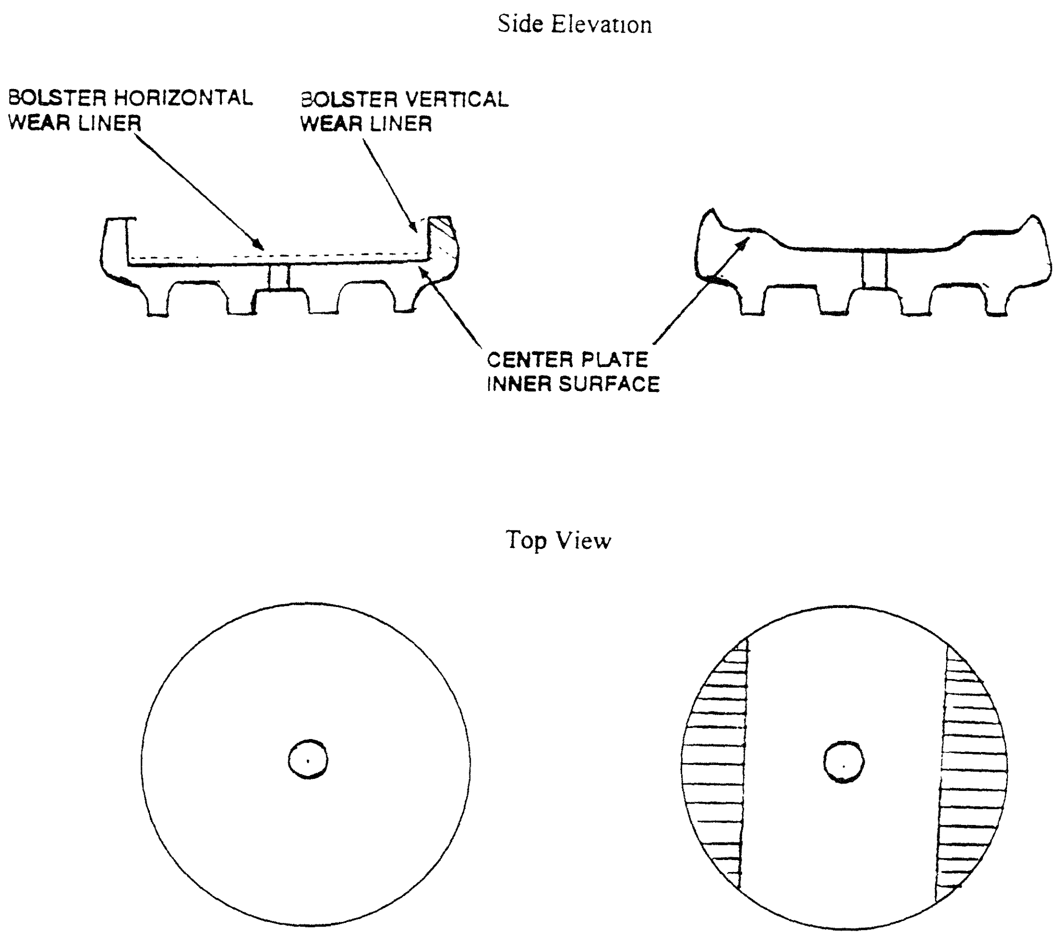
As mentioned previously, the bolster center plate not only functions as a pivot for the car body, but also carries the entire car body and loading weight into the truck structure. Although only a small rotating motion is sufficient in the center plate to permit trucks to negotiate even the sharpest curves, much concern is given to the plate's inner surface. Currently, the center plates for freight cars consist of casted inner surfaces covered by two abrasion resistant elastomeric center plate liners, i.e. bolster vertical wear liner and bolster horizontal wear liner. These two liners are also described in more detail in the following chapter.

3.2.2. Internal Condition and Measurement

As shown in figure 3.1., the condition on the central truck bolster areas can not be inspected directly without taking the car body off. Therefore, it is called internal condition in the thesis and the related parts are called internal parts (figure 3.3.). Among all the internal parts, center plate is the most vulnerable and hence important one as presented previously. The shape of a new bolster's center plate inner surface under the two wear liners is illustrated by the figure 3.8. (i). After an extensive time of operation, it tends to be worn into the shape as illustrated in figure 3.8. (ii). Unless the whole bolster is extremely worn and needs to be replaced, repair to the bolster is usually gauging, welding and rebuilding the center plate inner surface to the proper shape.

In practice, there are no universally applied measurements for the internal condition. In this research, the internal condition was defined by two methods. One is the nature of the repair work applied to the center plate area. For example, rewelding work taking more labor hours was considered as corresponding to more serious degree of wear than that taking less. The other is the total repair cost spent on internal parts.

Figure 3.8. Bolster Center Plate



(i) the shape of new center plate **(ii) the shape of worn center plate**

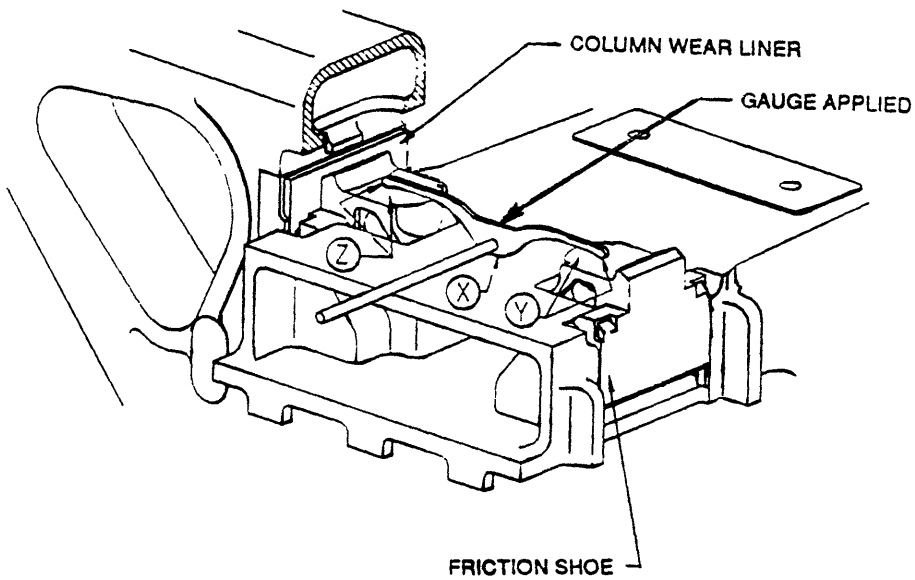
3.2.3. External Condition and Measurements.

As opposed to the internal parts and condition, the external condition is the condition of the externally visible parts including side frames, side parts of the bolster, etc. (see figure 3.3.). The external condition can to some extent be inspected directly without taking the car body off the car trucks.

There are some measurements for external condition employed in practice. First, the various wear liners located in side frames and truck sides can show the degree of wear on corresponding parts. Second, the inches of the wear on pocket outer wall is an index of the condition of the pocket(figure 3.6.). Several liners and the wear on pocket outer wall were used in the research and will be explained in more detail in the following chapters.

Another frequently used measurement is wedge rise (shoe height). Proper functioning of the truck is largely dependent on the satisfactory condition of the suspension system (figure 3.6.). The wear related to the system can take place on the following elements: 1) the column wear liner, 2)the friction shoe outer side, 3)the pocket slope, and 4)the bolster slope (cf. IEEE/ASME 1990). It can be seen that the first two elements contact and wear each other, and so do the second two. It is apparent that in all cases the wear is such as to permit the friction shoe to rise with a consequent relaxation of the spring and a reduction in the "column load". Along with the wear between the column wear liner and the friction shoe outer side and between the bolster pocket slope and friction shoe slope, the height that the friction shoe can rise tend to increase. Therefore, a measurement of the height between the top of the shoes and the top of the bolster, called wedge rise or shoe height, is a comprehensive measurement of the total suspension system area's wear. An easy method to check the wedge rise is to use a yoke gauge (figure 3.9.). In general, the system is considered in working order when the gauge contacts the bolster at "X". The function of the system still remains but repair is needed when the gauge contacts both friction shoes at "Y" and "Z" and the bolster at "X". Truck manufacturers usually specify a level of wedge rise at which the truck should be repaired or rebuilt, corresponding to the point at which some level (usually 50%) of the damping ability has been lost.

Figure 3.9. Checking Comprehensive Wear of Suspension System by Wedge Rise



Source: *ASF Maintenance and Repair Manual, Super Service Ride Control and Ride Control Trucks, 1994.*

3.3. Traditional Inspection and Maintenance Policy

In this section, the traditional inspection and maintenance policies are presented first. This is followed by the two problematic situations that incur costs which the proposed new policies seek to reduce.

The inspection policy for trucks is generally at the discretion of the car owner. Some car owners inspect trucks as part of periodic planned maintenance programs. Other car owners rebuild trucks at fixed interval to preserve a high level of ride quality. And some others inspect and rebuild trucks only at very long intervals as part of the general car overhaul. A general principle governing the inspection and rebuilding of trucks is to allow the truck to wear almost, but not quite, to the point where the bolster can not be renewed. This allows the car owner to minimize truck maintenance expenses without increasing bolster replacement. In general, the external condition of the car truck is inspected more frequently. The inspection for the internal condition and repair for both internal and external parts are done at repair shop without any anticipation to the true internal condition. External condition inspection is done much more frequently than the internal inspection and the overhaul.

Under this practice, a high level of cost may be incurred in the following two situations. The first is that a truck's internal condition is found to be still acceptable after the car body is removed from the truck at repair shop. Some repair and/or replacing work may still be done because the cost of disassembling the car and truck have been incurred anyway. In this case, the cost of removing the car from service and the additional repair have been incurred with very little subsequent benefit.

The second situation is that a truck's internal condition is actually in a poor state during the interval between two overhauls, but the owner of the car leaves the car in service. Extensive wear in the internal truck may cause problems in train operation, such as difficulty of pivoting/turning around the curves, derailment, damage to the track, car body or lading and truck "hunting". In addition to these comprehensively serious consequences, there may be a direct economic penalty if the truck is allowed to wear to such a poor condition that it can not be restored but must instead be replaced. It is not difficult to see that the key problem in either of the two cases comes from the difficulty in knowing the internal truck condition without disassembling the car and the truck. Since there are more than a million of railroad cars (hence trucks) running in the US, the effort of searching for a solution to the problem is potentially valuable.

3.4. Predictive Inspection Methods

The way proposed by the research to attack the problem is to predict the internal truck condition from the external condition inspection (without disassembling the car and truck). It is necessary to describe the underlying rationale for this proposition. Since the three-piece freight car truck is a complex mechanical system, the performance and wear conditions of its different parts are likely to be interactive and integrative from one to another. Internal bolster area is the only place taking all the weight of the car body and the freight loading, and all the forces are transmitted throughout the truck, especially the external area. Therefore, external conditions to some extent should be expected to reflect the overall performance of the internal bolster parts. This concept supports the predictive inspection approach for the internal bolster condition.

The key question is to find useful measurements for both internal and external truck conditions. Some measurements have been discussed generally in the previous section. Specifically in this thesis research, the wear condition of certain wear liners and the pocket outer wall were taken as external condition measurements. Wedge rise data was not available for the research. Internally, since the truck center plate is the most critical area, the condition around the center plate was taken as a reflection of the internal truck condition. Two types of the measurements were applied. One was the total cost for the all internal repairs, and the other was the degree of wear estimated from the nature of the repair work.

According to the two types of the internal truck condition measurements, three specific prediction methods were proposed, i.e. linear method, discrete choice method and performance threshold method.

For the total cost measurement, it was proposed to search for a linear relation between the external measurements and the total internal repair cost. By this relationship, a truck's internal repair cost could be predicted once its external measurements are observed.

If the internal condition is measured by the repairs done around center plate area, the prediction method would be discrete choice method and performance threshold method. Several states of the internal truck wear condition, e.g. "normal", "OK" and "abnormal", can be defined according to some criterion about the repair work. Discrete choice model seeks to find the link between the probabilities of internal truck condition being each state and external condition. The performance threshold method seeks to build a linear performance function of external variables and find certain thresholds for performance horizon, thereby to find the link between the threshold intervals which corrpond to each state and the external variables.

CHAPTER 4.

THEORETICAL BASIS FOR THE NEW PREDICTIVE INSPECTION TECHNIQUES

The proposed predictive inspection techniques are based on several underlying theories, which were mainly linear regression method, discrete choice method (cf. McFadden) and performance threshold method. Since linear regression is generally well known, this chapter is focused primarily on discrete choice and performance thresholds methods.

4.1. Discrete Choice Method

The basics of discrete choice method is first presented in one of its classical contexts of freight mode analysis. This is followed by a discussion of the theory's application in the railroad car truck context. Finally, some comparison is made between the two contexts.

4.1.1. Discrete Choice Analysis for Freight Mode Choice

The development of discrete choice theory has been closely tied with transportation. The theory has received very comprehensive application in transportation mode choice analysis (Ben-Akiva and Lerman, 1985). Transportation mode choice analysis seeks to explore the foundation on which either personal travelers or shippers make the mode choice decision for their trips or freight transportation. In this section, three basic concepts, deterministic utility, random utility and logit model, are presented in the context of freight transportation mode choice.

4.1.1.1. Deterministic Utility

Freight transportation mode choice analysis seeks to explore the basis by which shippers select a particular mode from a set of alternatives or choices for transporting their freight (Roberts, 1975; Vieira, 1993). The most frequently considered alternative modes are rail, truck and intermodal. For the convenience of exposition, the following presentation in this section uses an example choice set including these three modes. According to classical consumer theory in microeconomic analysis, every shipper will choose the alternative mode with the largest utility across the choice set. "Utility" is the term used by economists to describe the level of satisfaction or happiness derived from the consumption or use of a good or service. In case of the freight transportation shipper, the utilities of the modes are the satisfaction which the shipper receives from the service of the modes. For a freight shipper, this utility or satisfaction may take the form of minimized total logistics cost or some combination of cost and service requirement being met. Two types of variables are identified as the major factors influencing the utilities of the alternatives modes for the shipper. One is the attributes of each alternative, e.g. transit time (days), freight rate (dollar per ton), reliability (percentage of times shipments arrive when wanted) and safety and damage (percentage of shipment value). The other factor is the shipper's socioeconomic characteristics, e.g. the size of the shipper, the cost structure of the shipper and the nature of freight to be transported. The utility of each alternative can be expressed in a functional form of the variables of the two types. One example is as follows:

$$
\begin{aligned}
u^1 &= \beta_0 + \beta_1 x_1^1 + \beta_2 x_2^1 + \beta_3 x_3^1 + \cdots + \beta_k x_k^1, \\
u^2 &= \beta_0 + \beta_1 x_1^2 + \beta_2 x_2^2 + \beta_3 x_3^2 + \cdots + \beta_k x_k^2, \\
u^3 &= \beta_0 + \beta_1 x_1^3 + \beta_2 x_2^3 + \beta_3 x_3^3 + \cdots + \beta_k x_k^3,
\end{aligned}
\tag{4.1.}
$$

where u^1, u^2 and u^3 are the utilities of the modes rail, truck and intermodal for the shipper respectively; β_0, $\beta_1, \beta_2, \beta_3, \cdots \beta_k$ are unknown parameters which are to be estimated by discrete choice models; and $x_1^i, x_2^i, x_3^i, \cdots x_k^i$ (i =1,2,3) are the variables of the alternative's attributes and shipper's socioeconomic characteristics for each alternative i, e.g. x_1^1, x_2^1 and x_3^1 are transit time of the three modes.

One can note in the equation (4.1.) that the same variables in the equations of different alternatives have the same parameters. For example, the parameters for x_1^1, x_2^1 and x_3^1 are the same β_1. This implies that the same amount of change of transit time for each alternative will cause the same amount of change of utility of each alternative mode for the shipper. This is probably inappropriate in many cases in that one more hour transit time of the freight on the trucks is normally less acceptable for the shipper than that on the railroad cars. For this reason, two important concepts have been introduced, namely, alternative-specific variables and generic variables. A variable is called alternative-specific if it has different parameters in the utility functions for different alternatives, and generic if not. For example, we might expect that the utilities of the different modes would be different if all the values of the variables are the same across the alternatives. For this case, the concept of alternative-specific constant has been introduced. A constant term is called alternative-specific if it takes a different value in the utility functions for different alternatives. An example following equation (4.1.) is as follows:

$$
\begin{aligned}
u^1 &= \beta_0 + \beta_1 x_1^1 + \beta_2 x_2^1 + \beta_3 x_3^1 + \cdots + \beta_k x_k^1, \\
u^2 &= \beta_0' + \beta_1' x_1^2 + \beta_2 x_2^2 + \beta_3 x_3^2 + \cdots + \beta_k x_k^2, \\
u^3 &= \beta_0'' + \beta_1'' x_1^3 + \beta_2 x_2^3 + \beta_3 x_3^3 + \cdots + \beta_k x_k^3,
\end{aligned}
\tag{4.2.}
$$

where variables of transit time x_1^1, x_2^1 and x_3^1 are alternative-specific and have different parameters β_1, β_1' and β_1'' for the alternatives. The constant terms, β_0, β_0' and β_0'', are also alternative-specific and different across the alternatives.

As one can notice, there is no stochastic element involved in the utility functions discussed previously. Therefore, it is called deterministic utility theory. According to the theory, the utilities of the alternatives will be entirely determined if the values of all the alternative attributive and shipper socioeconomic variables are known. The alternative with the largest utility is then determined and chosen as well. It is usual to observe that shippers actually choose different alternatives from time to time with the variables unchanged . This led to the development of random utility theory, formalized by Manski (1977), in which the utilities of the alternatives are treated as random variables.

4.1.1.2. Random Utility Theory

In random utility theory, the utility is considered to consist of two components, a systematic (deterministic) component and a random (disturbance) component. The systematic component is the same as deterministic utility, a non-stochastic function formed of attributive and socioeconomic variables. A random variable is then added to each alternative's utility. An example is

$$
\begin{aligned}
u^1 &= \beta_0 + \beta_1 x_1^1 + \beta_2 x_2^1 + \beta_3 x_3^1 + \cdots + \beta_k x_k^1 + \varepsilon^1 &&= v^1 + \varepsilon^1, \\
u^2 &= \beta_0' + \beta_1' x_1^2 + \beta_2 x_2^2 + \beta_3 x_3^2 + \cdots + \beta_k x_k^2 + \varepsilon^2 &&= v^2 + \varepsilon^2, \\
u^3 &= \beta_0'' + \beta_1'' x_1^3 + \beta_2 x_2^3 + \beta_3 x_3^3 + \cdots + \beta_k x_k^3 + \varepsilon^3 &&= v^3 + \varepsilon^3,
\end{aligned}
\tag{4.3.}
$$

where the linear function forms of constants and variables, v^1, v^2 and v^3, are the systematic components, and $\varepsilon^1, \varepsilon^2$ and ε^3 are the random terms for each alternative.

With the utilities incorporating a stochastic component, every alternative has some possibility of being chosen by the shipper because each alternative has the chance to have the largest utility for the shipper across the choice set. Therefore every alternative mode will be chosen with the probability that its utility is larger than any other alternative's. For example, rail (mode 1) will be chosen over truck (mode 2) or intermodal (mode 3) by the shipper with the probability

$$\Pr(1) = \Pr(u^1 \geq u^2 \text{ and } u^1 \geq u^3). \tag{4.4.}$$

Mathematically and generally, alternative i would be chosen with the probability

$$\Pr(i) = \Pr(u^i \geq u^j), \text{ for all } j \neq i \text{ and } i, j \in (1,2,3). \tag{4.5.}$$

Given the probability of each alternative being chosen for each individual shipper in a shipper population, the aggregate demand of the population for a given mode is simply the summation of the probabilities of the mode being chosen across all the shippers in the population.

4.1.1.3. Logit Model

For the random utility theory to be practically useful, more concrete specification of the distribution of the random disturbance must be made. The most frequently used specification is Gumbel distribution (Johnson and Kotz (1970) and Domencich and McFadden (1975)) , namely,

$$f(\varepsilon) = \mu e^{-\mu(\varepsilon-\eta)} \exp[-e^{-\mu(\varepsilon-\eta)}], \tag{4.6.}$$

where μ and η are two parameters. If the disturbance term is assumed Gumbel distributed, then the difference between disturbance terms associated with two modes $\varepsilon^i - \varepsilon^j$ is logistically distributed.

Based on the assumptions above, the probabilities of each alternative being chosen will have the functional form

$$
\begin{aligned}
\Pr(i) &= \Pr(u^i \geq u^j) \text{ for all } j \neq i \\
&= \frac{e^{v^i}}{e^{v^1} + e^{v^2} + e^{v^3}} \\
&= \frac{e^{v^i}}{\sum_{j=1}^{3} e^{v^j}}.
\end{aligned}
\tag{4.7.}
$$

Equation (4.7.) shows that the probability of alternative i being chosen is equal to the proportion of the exponential value of alternative i's utility to the summation of the exponential values of all the alternatives' utilities.

A simple example of a logit model is presented below. Again, three alternatives, rail, truck and intermodal denoted by superscript 1,2 and 3 respectively, form the choice set of the model. Two independent variables, transit time and freight rate, are included.

$$
\begin{aligned}
u^1 &= \beta_0 \cdot 1 + \beta_0' \cdot 0 + \beta_1 t^1 + \beta_1' \cdot 0 + \beta_1'' \cdot 0 + \beta_2 r^1 + \varepsilon^1, \\
u^2 &= \beta_0 \cdot 0 + \beta_0' \cdot 1 + \beta_1 \cdot 0 + \beta_1' t^2 + \beta_1'' \cdot 0 + \beta_2 r^2 + \varepsilon^2, \\
u^3 &= \beta_0 \cdot 0 + \beta_0' \cdot 0 + \beta_1 \cdot 0 + \beta_1' \cdot 0 + \beta_1'' t^3 + \beta_2 r^3 + \varepsilon^3.
\end{aligned}
\tag{4.8.}
$$

where t^i and r^i are the transit time and freight rate for alternative mode i.

Because only the differences between the utilities actually affect the shipper's choice, a logit model essentially estimates the parameters using the differences between the same kind of variables across the utilities' equations. Therefore, if there are three alternatives and three utility equations associated in a model, there will end up with only two equations in difference form containing all the information necessary for estimation. Notice that there was not a third constant term, say $\beta_0'' \cdot 1$, in the third equation of (4.7.). The reason for this is that the third constant will cause perfect collinearity and render the model inestimable. This also holds true for the alternative specific dummy variables.

The above model specification is presented in table 4.1, with the format used throughout the remainder of this thesis. Table 4.1. shows that two alternative specific constants β_0 and β_0' are included. This implies that the utilities of different alternatives are different if all the other variables are the same. Transit time is included as three alternative specific variables β_1, β_1' and β_1'' each for one alternative mode. This implies that the same amount of change of transit time on different modes influences shipper's utilities for them differently. Put in another way, the value of transit time is perceived differently by the shippers from one mode to another. Finally, rate is included as a generic variable across the alternatives. This implies that the same amount of the rate changes for different modes influence the shipper's utilities for them to the same degree, a implication which seems reasonable.

Table 4.1. Model Specification for An Example Discrete Choice of Freight Transportation Modes

Utilities	β_0	β_0'	β_1	β_1'	β_1''	β_2
1. Rail	1	0	Transit time by rail	0	0	Freight rate by rail
2. Truck	0	1	0	Transit time by truck	0	Freight rate by truck
3. Intermodal	0	0	0	0	Transit time by intermodal	Freight rate by intermodal

4.1.2. Discrete Choice Analysis in the Context of Railroad Truck Inspection.

As presented in Chapter 3, the new predictive inspection technique defines several states of internal bolster condition, and then predicts the probability of the internal bolster condition being in each state from the external measurements which can be determined easily. To do this, discrete choice analysis was applied.

Analogous to the freight mode choice example, pre-defined states of internal bolster condition are considered as the alternative choices and the external measurements the independent variables. It needs to be mentioned that the terms "alternative" and "choice" correspond to "mode" and "state" in freight modes and railroad truck cases, respectively. Similar to the concept “utility” in mode choice context, the concept "tendency" is defined in the freight car truck context. Intuitively, one may think of tendency as the likelihood that the truck internal bolster condition would be in a certain state. Similarly, the tendency consists of two components, a systematic and a random component. The systematic component is represented as a function of the external inspection variables. The random component is simply a random variable.

In analogy to the previous discussion for freight mode choice, an example of internal condition state model is presented below. Three states, "good", "OK", and "bad", and one illustrative variable of external measurements, wedge rise(w) is included in the model.

Similar to (4.8.), the tendencies for three internal states are defined as follows.

$$
\begin{aligned}
T^1 &= \alpha_0 \cdot 1 + \alpha_0' \cdot 0 + \alpha_1 w + \alpha_1' \cdot 0 + \alpha_1'' \cdot 0 + \varepsilon^1 = d^1 + \varepsilon^1 \\
T^2 &= \alpha_0 \cdot 0 + \alpha_0' \cdot 1 + \alpha_1 \cdot 0 + \alpha_1' w + \alpha_1'' \cdot 0 + \varepsilon^2 = d^2 + \varepsilon^2, \\
T^3 &= \alpha_0 \cdot 0 + \alpha_0' \cdot 0 + \alpha_1 \cdot 0 + \alpha_1' \cdot 0 + \alpha_1'' w + \varepsilon^3 = d^3 + \varepsilon^3.
\end{aligned}
\tag{4.9.}
$$

where T^i are the tendencies of internal condition being in state i, d^1, d^2 and d^3 are deterministic components of the tendencies, w is wedge rise and ε^i are random disturbances (i=1,2,3).

Similar to (4.7.), the probability of the internal bolster condition being in state i is the probability that tendency to be in state i is larger than tendency to be in any other state. This is given by

$$\begin{aligned}\Pr(i) &= \Pr(T^i \geq T^j) \qquad \text{for all } j \neq i \\ &= \frac{e^{d^i}}{e^{d^1} + e^{d^2} + e^{d^3}} \\ &= \frac{e^{d^i}}{\sum_{j=1}^{3} e^{d^j}}.\end{aligned} \tag{4.10.}$$

The model specification is shown in table 4.2. Two alternative specific constants are included. Wedge rise is specified as alternative specific with the rationale that the change of wedge rise influences the tendency of each state differently.

Table 4.2. Model Specification for An Example Discrete Choice of Internal Condition State

Tendency	α_0	α_0'	α_1	α_1'	α_1''
1.Good	1	0	Wedge rise	0	0
2.OK	0	1	0	Wedge rise	0
3.Bad	0	0	0	0	Wedge rise

4.1.3. Comparison Between the Discrete Choice Analysis in the Contexts of Freight Modes and Railroad Truck Internal Condition State.

It is easy to see the similarity between the discrete choice analysis in the context of freight modes and truck internal bolster condition states. But some difference still exists. The major difference lies in their different underlying behavioral implications. Discrete choice model for freight mode is supported by a strong behavioral theory, namely, consumer utility theory. A strong causal relationship is known to exist between utilities (hence actual choice) and the independent variables - attributes of alternatives and the shipper's socioeconomic characteristics. Each variable partially determines the shipper's actual choice. On the other hand, there is no analogous mechanical or physical theory underlying the discrete choice model used for truck internal states. The reason for this is that the relationship between internal bolster states and external measurements are not causal. Rather, the internal states and external measurements are more likely to be different indices of the truck's overall performance and condition. Another difference lies in the nature of the alternatives in the two contexts. Strictly speaking, alternative shipping modes are absolutely discrete. Internal condition is defined into several alternative internal states according to some essentially artificial criteria. Ideally, internal condition should be measured as a continuous variable, or practically discrete ordinal levels, ranging from excellent, good, OK to bad. As we will see, this weakness is addressed by the performance threshold method.

4.2. Performance Threshold Method

In this section, the introduction to the problem and basic idea of the performance threshold method is presented first. This is followed by the presentation of the theoretical basic of the method. Finally, a simple example is presented.

4.2.1. Introduction and Basic Idea

In many statistical inference applications, the dependent variable, which is otherwise essentially continuous, falls in some ordinal levels of intervals. The ordinal nature is normally due to methodological limitations in data collection, which forces the researcher to lump together and identify various levels for the dependent variable. The truck condition inspection may be considered as a case of this.

As presented previously, the internal truck condition is ideally a continuous measure. But as will be seen in chapter 5, the repair data from which we can get information about the condition only supports a series of ordinal levels of states of the condition. More formally, it is assumed that a variable **performance** can be defined as an index of the operational quality of the internal truck area. **Performance** is a continuous variable. It can not be observed but may be indicated by external truck condition. Nonetheless, only several ordinal states of condition, e.g. "**normal**", "**bad**" and "**poor**", can be obtained from the repair data to reflect the **performance** (this will be more clear after reading the following chapters). In this case, traditional linear regression which seeks a linear relationship between the performance and external measurement variables is inappropriate in that the dependent variable is assumed to be continuous.

A statistical method, called **ordinal probit method** in general econometric terminology, was proposed by McKelvey and Zavoina (1975). The method is called throughout the thesis **performance threshold method** due to its application to the machinery inspection context.

The basic idea of the method is as follows. It is assumed that the internal performance can be indicated by the external condition, and therefore the performance function is assumed to consist of two parts: a deterministic and a stochastic part. Similar to the discrete choice method, the deterministic part of a performance function takes a linear functional form of the external measurement variables, and the stochastic part is just a random disturbance term with certain presumed distribution. The performance function can be shown as follows:

$$P_n = \sum_{k=1}^{K} \beta_k x_{kn} + \mu_n \ . \qquad (4.11)$$

where

P_n = the performance of internal area of truck n.

x_{kn} = the kth external measurement variable, $k = 1, 2 \cdots K$.

β_k = the parameter for the external variable x_{kn}, $k = 1, 2 \cdots K$.

μ_n = the random disturbance term for the underlying performance function of internal area of truck n.

Although the performance is essentially continuous, it is assumed that there exist some thresholds which divide the full spectrum of the performance into several ordinal intervals (states) as in the above example. These ordinal states are suggested by the internal repair data. The method is to estimate the parameters in the underlying performance function and the thresholds identifying the states. With the parameters and thresholds known, the internal state for a truck can be predicted once its external measurement variables are observed. The performance value can be easily obtained by inserting external variables into the estimated underlying performance function. Comparing the performance value to the estimated thresholds, the internal truck condition is predicted to be in the state corresponding to the threshold interval into which the performance falls.

4.2.2. Performance Threshold Method

Given a sample of N observations and the performance function shown as equation (4.11.), it is further assumed that the random disturbance term of the underlying performance function is normally distributed,

$$\mu \sim N(0,\sigma). \tag{4.12}$$

However, similar to the concept of utility, performance can not be observed. Instead, the ordinal states defined from the observable repair data are assumed to be the **indicators** of the underlying performance. Then the observed indicators, are associated with the underlying performance function by defining a series of thresholds. Each threshold interval (formed by two contiguous thresholds) corresponds to a internal state. The internal condition is assumed to be in the state into whose corresponding threshold interval the performance value falls. If M ordinal states and hence M thresholds levels are identified, then there will be $M-1$ thresholds. This can be shown as follows:

$$-\infty = t_0 < t_1 < t_2 \cdots < t_{M-1} < t_M = +\infty \, , \tag{4.13.}$$

where

$t_1,\ t_2 \cdots t_{M-1}$ = thresholds for the performance. And

$$C_n \in S_m \Leftrightarrow t_{m-1} \le P_n \le t_m \, , \tag{4.14.}$$

where

C_n = observed internal truck state for truck n.

S_m = ordinal state m defined from repair data.

t_{m-1} = lower bound threshold for the performance corresponding to the ordinal state m, and

t_m = upper bound threshold for the performance corresponding to the ordinal state m.

Since the states are ordinal, they can be represented as a series of dummy variables as follows:

$$C_{nm} = \begin{cases} 1 & \text{if } C_n \in S_m \\ 0 & \text{otherwise} \end{cases} \, , \tag{4.15.}$$

meaning for truck n, dummy variable C_{nm} will equal 1 if the truck's internal condition is in state m.

From equations 4.11. to 4.15., it can written

$$
\begin{aligned}
C_{nm} = 1 \Leftrightarrow C_n \in S_m \Leftrightarrow t_{m-1} \le P_n \le t_m \\
\Leftrightarrow t_{m-1} \le \sum_{k=1}^{K} \beta_k x_{kn} + \mu \le t_m \\
\Leftrightarrow t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn} < \mu < t_m - \sum_{k=1}^{K} \beta_k x_{kn} .
\end{aligned}
\tag{4.16.}
$$

Since μ is assumed normally distributed , the probability of the machine's condition being in state M is given by

$$
\begin{aligned}
\Pr(C_{nm} = 1) &= \Pr\left(t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn} < \mu < t_m - \sum_{k=1}^{K} \beta_k x_{kn} \right) \\
&= \Pr\left(\frac{t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn}}{\sigma} < \frac{\mu}{\sigma} < \frac{t_m - \sum_{k=1}^{K} \beta_k x_{kn}}{\sigma} \right) \\
&= \Phi\left(\frac{t_m - \sum_{k=1}^{K} \beta_k x_{kn}}{\sigma} \right) - \Phi\left(\frac{t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn}}{\sigma} \right),
\end{aligned}
\tag{4.17.}
$$

Where $\Phi(\ )$ represents the cumulative standard normal distribution function. Assuming further, without loss of generality, that $t_1 = 0$ and $\sigma = 1$, the final model is given by

$$
\Pr(C_{nm} = 1) = \Phi\left(t_m - \sum_{k=1}^{K} \beta_k x_{kn} \right) - \Phi\left(t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn} \right), \tag{4.18.}
$$

Equation (4.18.) shows that the probability of the internal condition of truck n being in state M is equal to the difference of standard normal cumulative function valued at two points. The first point $t_m - \sum_{k=1}^{K} \beta_k x_{kn}$, is the difference between the upper threshold of the internal M and the deterministic part of the performance function (a linear function of the external variables). The second point $t_{m-1} - \sum_{k=1}^{K} \beta_k x_{kn}$, is the difference between the lower threshold of the internal M and the deterministic part of the performance function.

Maximum likelihood estimation is normally used to estimate the parameters and thresholds. With respect to the parameters and thresholds, maximizing the likelihood function given by

$$L = \prod_{n}^{N} \prod_{m}^{M} \left[\Pr(C_{nm} = 1)\right]^{C_{nm}} , \tag{4.19.}$$

produces the estimations.

A simple example of the performance threshold method is presented below. Suppose the internal condition of a machine is defined into three ordinal levels, good, OK, and bad. Two external variables, temperature and noise, can be inspected from outside of the machine. A performance threshold model can be built to capture the relationship between the internal states of condition and the external variables.

The performance function for the machine can be defined as follows:

$$P = \beta_0 + \beta_1 \cdot T + \beta_2 \cdot N + \mu , \tag{4.20.}$$

where P is the underlying performance; T and N are the temperature and noise inspected from the surface of the machine, respectively; β_0, β_1 and β_2 are the unknown parameters to be estimated; and μ is the random disturbance term assumed normally distributed. Since there are three ordinal states, two thresholds, t_1 and t_2, can be defined as follows:

if $P < t_1$, the internal condition of the machine is considered in "good" state, if $t_1 \leq P \leq t_2$, the internal condition of the machine is considered in "OK" state,

and if $P > t_2$, the internal condition of the machine is considered in "bad" state.

Given a sample of the condition of the machine (each observation contains the internal state inspected by actually disassembling the machine and external variables inspected directly), three parameters β_0', β_1' and β_2' and two thresholds t_1' and t_2' can be estimated.

Suppose an observation of the temperature and noise is made as T' and N', the estimated value of the performance of the machine is given by

$$P' = \beta_0' + \beta_1' \cdot T' + \beta_2' \cdot N'. \tag{4.21.}$$

Therefore, the internal condition state of the machine can be predicted as follows:

if $P' < t_1'$, the internal condition of the machine can be predicted in "good" state, if $t_1' \leq P' \leq t_2'$, the internal condition of the machine is predicted in "OK" state, and if $P' > t_2'$, the internal condition of the machine is predicted in "bad" state.

Chapter 5

Data

This chapter describes the data set of a research case study that the new predictive inspection techniques were applied to. As shown in chapter 3, both internal bolster condition data and external measurement data are necessary for applying the new predictive inspection techniques. In the practice of the railroad industry, rail cars are periodically inspected and repaired. Inspection reports and repair reports, or billing repair cards, contain potentially useful data for external measurements and internal bolster condition, respectively. The research of this thesis was based on data derived from the inspection and repair reports provided by a Canadian private car owner, Sultran Ltd. In this section, general information about the company is presented first. This is followed by the description of the raw data from the inspection and repair reports. Finally, the procedure by which a computer-usable data set was made out of the raw data is presented.

5.1. Description of Sultran LTD.

Sultran, Ltd is a Canadian producer and shipper of sulfur. It runs and operates a fleet of approximately 1000 cars. The cars are rotary coupler gondola cars equipped with barber S2HD trucks with oversize friction casting and D5 springs (some have heavier springs). The cars are divided into two populations by age and type, with the newer cars better equipped for heavy duty service. The cars are used to transport sulfur, which is corrosive, and are maintained at a shop owned by Sultran. In the late 1980's, it was decided to undertake an extensive inspection and rebuilding program. Most of the cars were scheduled for one overhaul after 650,000 to 700,000 miles of service.

5.2. Raw Data

Inspection and repair reports of 222 trucks (two trucks for each of 111 cars) were provided by Sultran for the research. The information about the trucks' external measurement and internal bolster condition were considered contained by the inspection and repair reports, respectively. In this section, the two reports are presented and analyzed intensively, and then the data set made out of the reports is presented.

5.2.1. Inspection Report

Periodically, the condition of various external parts of the rail car is inspected by Sultran in its loading yard. The results from the inspection are entered into standardized inspection report forms. The inspections used by this research were conducted in 1990 and 1992. During this time period, the format of the inspection reports was changed significantly and the content slightly. Therefore the inspection reports used by the research had two different formats, referred to as the 1990 and 1992 formats. Sample inspection reports in the two formats are included as Figure 5.1. and 5.2.

As shown by the figures, three major external areas were inspected, i.e., the couplers, the external parts of the truck and the car body. Since truck condition was the major object of this research, it was necessary to explain in more detail the inspection on external parts of the truck. In practice, there are several inspection measurements for external parts of the truck. The inspection report for this thesis contained three of them. They were called "wear plates", "inches of wear in pocket area", and "ceiling wear plates" in the reports of 1990 format, and "pocket wear plates", "pocket outer wall" and "roof

Figure 5.1. Inspection Report in 1990 Format.

REVIEW OF WEAR CONDITIONS ON SULX CAR SERIES 1000

CAR NUMBER ______ MILEAGE ___________ DATE INSPECTED ________

WEAR NOTED AS FOLLOWS

COUPLERS A end ____

B end ____

TRUCK SIDES AL ____

AR ____

BL ____

BR ____

TRUCK

BOLSTERS AL ____

AR ____

BL ____

BR ____

BODY CENTER

PLATE A end ____

B end ____

BOTTOM END

CATE A end ____

B end ____

PRIORITY FOR SHOP KWPAIRS ____________________________________

OTHER COMMENTS ____

Figure 5.2. Inspection Report in 1992 Format.

SULTRAN

Inspection Reports

Coupiers	A ______	B ________
coupier carrier W. F.	A________	B ________
Center Plate	A ________	B ________

Side Sill

Trucks	**AR**	**AL**	**BR**	**BL**
Friction Castings				
Column Wear Plates				
Pocket Wear Plates				
Pocket Outer Wall				
Roof Pedestal Liners				
Roller BRG. Adapters				

Other ____

Bottom Door	A ________	B ________

pedestal liner" correspondingly in the reports of 1992 format. It needs to be mentioned that the names of the three measurements in 1992 format are used throughout the thesis.

Pocket wear plate is the wear plate located between the bolster slope pocket and the slope surface of the friction shoe . There are two pocket wear plates on each side of a truck. When the bolster moves up and down, the force is absorbed by the spring group between the bolster and the bottom of the truck side frame and the springs below the friction shoes. When the friction shoes move up and down together with the bolster, the slope surfaces of the shoes wear with the pocket wear plates, and the outer walls of the shoes wear with the column wear plates located in the inner wall of the columns of the side frame. Column wear plates are also used as a measurement for external truck condition although it was not included in the inspection for this research. In the report, the condition of the two pocket wear plates on each end of the truck were measured with various qualitative and descriptive judgment such as "both OK", "both worn out", "one miss / one worn out", "one good / one worn", etc.

Pocket outer wall is the surface between the corners of friction shoes and slope pockets (figure 3.6.). When friction shoes and slope pockets move up and down, pocket outer wall is subject to wear. In the report, the wear on the pocket outer wall was measured by the depth of the wear with one unit as 1/16 inch.

Roof pedestal liner is the wear plate located between the side frame pedestal and wheel adapter (figure 3.4.). There are two roof pedestal liners on each side of a truck. When the train runs, the wear between the side frames and wheels bearing adapters can be taken mostly by the roof pedestal liners. In the report, the wear of roof pedestal liners was also measured with various qualitative and descriptive judgment such as "both OK", "both light wear", "one wear / one OK", "both worn out", etc.

In the reports of 1990 format, the above three measurements were included under the titles "truck sides" and "truck bolster". Roof pedestal liner was entered into "truck side" and pocket wear plates and pocket outer wall were entered into "truck bolster". It needed to be clarified that the term "truck bolster" in the inspection reports referred to the external parts of the bolster such as pocket outer wall, rather than internal bolster area such as center plate. In the reports of 1992 format, these measurements were included in a table with the upper-left cell "truck ...". The rows below the cell are various external measurements. The four columns to the right of the cell describe the locations of the measurements. For example, the cell lying in the column "AR" and row "roof pedestal liner" was entered by the measurement on the roof pedestal liner located at the left side of the A end truck.

5.2.2. Repair Report

When a car is sent to the repair shop for overhaul, the trucks will be disassembled entirely and repairs done on both the internal and external parts. It is in the repair shop that the true internal condition can be discovered. The information about the repairs is recorded onto a repair report, or more precisely, billing repair card. In general, three kinds of information are contained in the report: general location of the repair on the car, description of the repair and the cost associated with the repairs. A sample page of billing repair card is included as figure 5.3.

General location of the repair is usually represented by the end - A or B - and the side - R or L - of the car. In terms of the description of the repair, three elements - repair **job code, qualifier code** and **description** - show specifically what parts and how they were repaired. Stipulated by A.A.R. (Association of American Railroads) in the **Field Manual of the Interchange Rules**, four-digit repair job codes are assigned to the frequently applied repair jobs and two-letter qualifier codes are used to specify the detailed locations for the car parts. In addition to repair job codes, descriptions provide the most specific explanation of the repairs. The cost associated with the repairs includes labor cost - the labor hours and the associated charge - and material costs - material description and the price.

Following the research direction presented previously, we were specifically interested in the internal bolster condition among all the internal parts. Furthermore, it was mentioned in chapter 2 that the most vulnerable and critical part in internal bolster area is the bolster center plate. This was also shown by the observation that the repair on the

Figure 5.3. Sample Page of Billing Repair Card (Repair Report)

JOB NO.	LOC ON CAR	QTY	COND CODE	JC APPLD	QA	DESCRIPTION OF REPAIRS	WM	JC REMVD
110	B	44.00	0	4808	FF	RENEW BOLSTER VERTICAL WEAR LINER	2	4808
110	B	1 00	1	3570	EJ	APPLY HOZ. BIOLSTER WEAR LINER	9	3570
110	BR,L	48.00	0	4800	ZC	APPLIED POCKET WEAR LINER	1	4800
110	BR,L	4.00	0	4450	ZC	BUILD UP POCKET OUTER WALL	1	4450
110	u	8 00	0	450	ZC	BUILD UP BOLSTER GIBS	1	4450

QR	RES	NET CHARGES	LABOR HOURS	TY	MATERIAL DESCRIPTION	PDS PART#	PRICE
FF	1	154 00	2 20	1	VERTICAL WEAR RING S.S.14' 1-1/8' X 14'	3999EA0111	45 80
EJ	1	14 00	0 20	1	WEAR LINER BOLSTER HORIZ'L 14' F-1858-11	3570EJ0011	54.49
ZC	1	134 40	1 92	4	WEAR LINER, BOLSTER POCKET S.S.	3556EA0011	86.44
ZC	1	175 00	2 50				0.00
ZC	1	210.00	3.00				0.00

bolster center plate were recorded in almost all the repair reports provided and very few other miscellaneous repairs were done, such as replacing the crosskey. In most of the reports provided, the repairs related to bolster center plate were rewelding or replacing around two parts - **bolster center horizontal wear liner** (**BHWL**), a plate sitting on the bottom of the center bowl, **and bolster center vertical wear liner** (**BVWL**), a ring-shaped wear plate attaching to the inner wall of the center plate. Both liners are made from elastomeric mateial. It is necessary to clarify the true implication of entries of "rewelding" and "replacing" around two liners in repair reports. The repairs were normally done by the following procedure. Both liners were first taken away and the wear condition of the inner surface of bolster center plate (see chapter 3) underneath the two liners was investigated, respectively. Then corresponding gouging and rewelding were applied to rebuild the inner surface to normal. Finally, if the liners were found still in very good shape, they were put back into the center plate and "rewelding work of certain labor hours" was entered into the repair reports. If the liners were found not in very good shape, they were replaced with new ones and "replacing work of certain labor hours" was entered. For the convenience of presentation, the former case is referred to as **rewelding case** and the latter **replacing case** throughout the remainer of the thesis. It could be noticed that rewelding work was also applied in the replacing case. For either bolster vertical wear liner or bolster horizontal wear liner area, the various labor hours (hence labor charge) were taken and no material cost was incurred for rewelding case, while normally more labor hours were taken and certain material cost was incurred for replacing case. Therefore, combining the conditions of two liners and the real inner surface of the center plate underneath the liners, the overall internal bolster wear condition was normally considered worse in replacing case than in rewelding case. In general, the information of internal bolster condition that was specifically important for the research was what repair - rewelding or replacing - was applied and how many labor hours (hence labor charge) and material cost were incurred. By this information, we may estimate, though not precisely, the true internal bolster condition.

5.2.3. Raw Data Set

Out of the inspection and repair reports, a raw data set was made. As presented previously, the new predictive inspection technique was designed to construct the relationship between the internal bolster condition and the truck external measurements. The external measurements, which would be the independent variables for further modeling analysis, were based on the measurements provided by the inspection reports. The measurements were applied to the pocket wear plates, pocket outer wall and roof pedestal liners on both right and left sides of the trucks. In terms of internal bolster conditions, repair cost on internal bolster area would be used as the dependent variable in the linear modeling method. It was obtained by simply summing the labor and material costs shown in repair reports. For discrete choice and performance threshold methods, the states of internal bolster condition would be used as the dependent variable in the discrete choice modeling analysis. Since the major reflection of the internal bolster condition were the repairs around bolster center plate, bolster vertical wear liner and bolster horizontal wear liner were used to identify the states of the internal bolster condition. The raw data was organized into the format illustrated as table 5.1.

The first observation in the table 5.1. is presented as an example. The observation is the A end truck of car number 1000. The inspection for the truck was made on May 14, 1992. The six external measurement variables were found by the inspection as follows. The condition of the two pocket wear liners on the right side of the truck were both OK. Two sixteenth inches of wear on the pocket outer wall on the right side of the truck was found. The conditions of the two roof pedestal liners on the right side of the truck were both acceptable (good). The remaining three variables on the left side of the truck were measured in the same manner. In terms of the internal bolster condition, the first column was simply the repair cost spent on the internal bolster parts, Canadian $C 107.06. It was followed by the states of internal condition reflected by the conditions around bolster vertical wear liner area (BVWL) and bolster horizontal wear liner (BHWL) area.

Specifically, rewelding work of 1.1 labor hours was done around BVWL area and the replacing work of 0.2 labor hours was done around BHWL area.

Table 5.1. Sample Raw Data Made from the Inspection and Repair Reports

			External Measurements						Internal Measurements				
			Pocket Wear Liner, R (1)	Pocket Outer Wall, R	Roof Pedestal Liner, R	Pocket Wear Liner, L (1)	Pocket Outer Wall, L	Roof Pedestal Liner, L	Total Internal Repair Cost	Repair around Internal Bolster Center Plate			
										BVWL (2)		BHWL (3)	
Car No.	Inspect. Date	A/B End								Work	Hour(4)	Work	Hour
1000	5/14/92	A	2 OK	2	2 OK	2 OK	1	2 OK	107.06	rw (5)	1.1	rp (6)	0.2
		B	2 OK	1	2 OK	2 OK	1	2 worn out	107.06	rw	1.1	rp	0.2
1002	5/12/92	A	2 OK	2 OK	2 worn out	2 OK	2	2 OK	168.08	rw	1.5	rp	0.2
		B	1miss/1loose	2 OK	2 worn	1miss/1loose	2	2 worn out	96.56	rw	1.1	rw	0.32
1049	9/29/92	A	2 OK	2	2 OK	1miss/1worn	3	2 OK	77.00	rw	1.1	no repair	
		B	2 OK	2	2 OK	1miss/1worn	3	2 worn out	145.49	rw	1.1	rp	0.2
1006	11/24/90	A	2 good	2	2 OK	2 good	2	2 lite worn	259.55	rp	2.2	rp	0.32
		B	2 good	4	2 OK	2 loose	3	2 lite worn	2214.17	rp	2.2	rw	0.32

Note: (1). R(L): right (left) side of the truck,

(2). BVWL: bolster vertical wear liner,

(3). BHWL: bolster horizontal wear liner,

(4). Hour: labor hour,

(5). rw: rewelding work,

(6). rp: replacing work.

5.3. Data Set

In order to implement the models proposed previously, it is necessary to make a computer-software readable data set out of the raw data. To do that, for each of the external variables measured with qualitative and descriptive judgments, several categories were identified and applied. Also, several categories for the states of internal bolster condition were applied. Therefore the variables measured qualitatively in the raw data would be assigned numbers by the categories. The values of the variables measured numerically in the raw data were directly transferred into the data set.

5.3.1. External Measurement(Independent) Variables

The external (independent) variables consisted of the measurements found by the inspection for the pocket wear liners, roof pedestal liners and pocket outer wall. The entries for the pocket wear liners, precisely speaking, for the two liners on the same side of the same (A or B) truck, were categorized into one of three groups. The first group corresponded to the situation that both liners were in good or OK condition. The corresponding qualitative representations in the raw data were "2 good", "2 OK", "2 present", etc. The second group corresponded to the situation that one liner was in good or mediocre condition but the other bad. The corresponding qualitative representations in the raw data were "1 good /1 worn out", "1 OK/1 miss", "1 present/1 broken", etc. The third group corresponded to the situation that both plates were in bad condition. The corresponding qualitative representations in the raw data were "2 worn", "2 miss", "1 miss/1 worn out", etc. These three groups were named "fine ", "problematic" and "poor", and assigned values 1, 2 and 3 in the data set, respectively.

The entries for the two roof pedestal liners, precisely speaking, for the two liners on the same side of the same truck, were categorized into one of three groups as well. The first group corresponded to the situation that two liners were both in good condition. The corresponding qualitative representations in the raw data were "2 OK", "2 new", etc. The second group corresponded to the situation that one liner was in OK condition and the other bad or both slightly bad. The corresponding qualitative representations in the raw data were "2 light worn", "2 partly worn", "1 worn/1 OK", etc. The third group corresponded to the situation that both liners were in bad condition. The corresponding qualitative representations in the raw data were "2 worn out", "2 worn", "2 miss", etc. These three groups were named "fine", "problematic" and "poor", and assigned 1, 2, and 3 in the data set, respectively.

The entries for the pocket outer wall in the data set were directly transferred from the raw data since they were measured numerically in the raw data set with one unit equal to 1/16 inch of wear.

5.3.2. Internal Bolster (Dependent) Variables

The repair costs of the internal bolster parts were selected as the internal (dependent) variables for the linear models, and the states of internal bolster condition for discrete choice models and performance threshold models. The repair costs on the internal bolsters parts were given in Canadian dollars. They were directly transferred from the raw data into the data set.

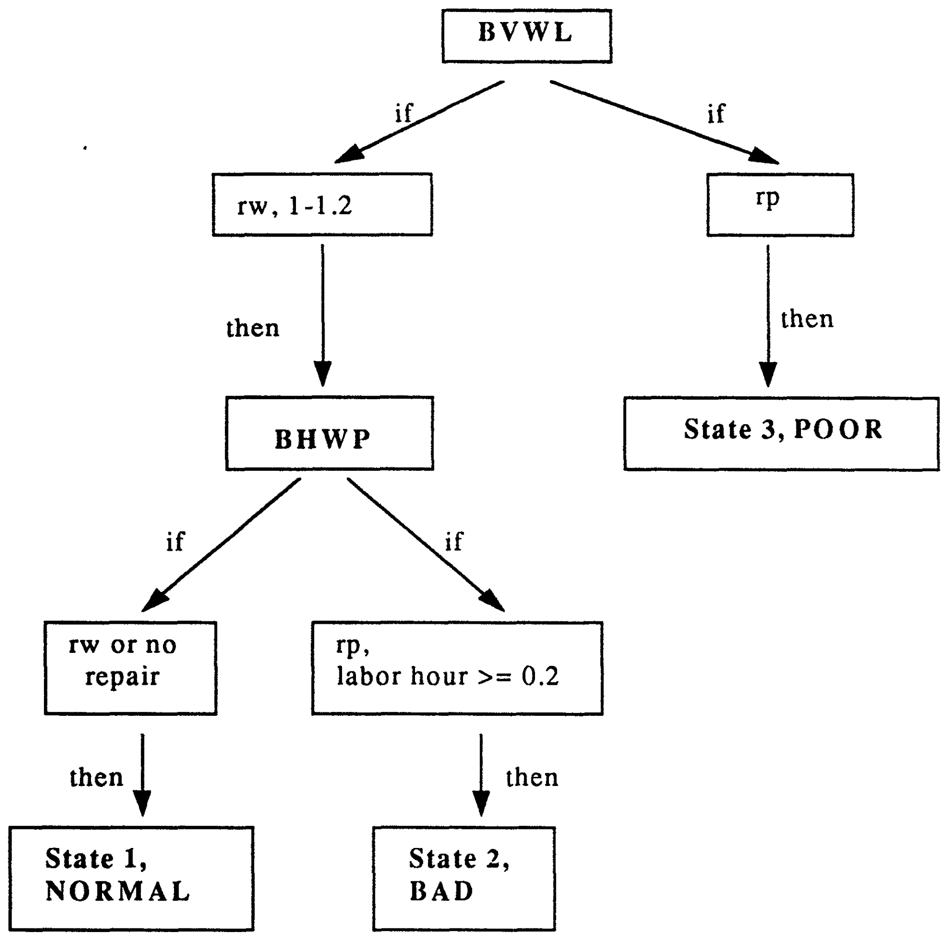
Before the data entry procedure for the states of internal bolster condition is presented, it is necessary to make some important observations on the states of internal bolster condition in the raw data set (see table 5.1.). For bolster vertical wear liner area (BVWL), three cases were included in the raw data, i.e. no repair applied, rewelding, and replacing, corresponding to increasingly serious wear conditions. There were many more "rewelding" and "replacing" cases than "no repair" cases. One to 1.2 labor hours were taken for almost all the rewelding cases and 2.2 labor hours were taken for all the replacing cases. For bolster horizontal wear liner area (BHWL), the same three cases were involved. There were many more "replacing" cases than "rewelding" and "no repair" cases combined. Among replacing cases, either 0.2 or 0.32 labor hours were taken. By comparison between the wear conditions on BVWL and BHWL areas, it was observed that wear condition was normally less serious around BVWL area than around BHWL area. In the raw data set, most of the trucks whose BVWL was in rewelding case had

BHWL in replacing case. And most of the trucks whose BVWL is in replacing case normally had BHWL in replacing case as well (see table 5.1. for an example).

Based on these observations, the states of the internal bolster condition were categorized into three groups. The first group corresponded to the situation that the condition of BVWL in raw data was entered "rw, 1-1.2" (rewelding work of 1-1.2 labor hours) and the condition of BHWL was entered either "rw" (rewelding work, regardless of the labor hours associated) or "no repair". The second group corresponded to the situation that the condition of BVWL in raw data was entered "rw, 1-1.2" (rewelding work of 1-1.2 labor hours) and the condition of BHWL was entered "rp" (replacing work, regardless of the labor hours associated). The third group corresponded to the situation that the condition of BVWL in the raw data was entered "rp" (replacing work on BVWL, regardless of the labor hours associated and the condition of BHWL). These three groups were named "normal", "bad", and "poor ", and assigned values 1, 2 and 3 in the data set, respectively. Figure 5.4 illustrates the categorization of internal states.

Two major reasons for such categorization for the internal bolster states should be mentioned. One reason was that given a data set of moderate size, such a categorization made each state have an acceptable number of observations to estimate the model reasonably. The other reason was that such a categorization provided a state (choice) set containing identifiable and meaningful states, which are necessary for properly applying discrete choice method. By such categorization, each state could be distinguished from all the others in the state set since there was no overlapping among them. In addition, with respect to the same area (BVWL or BHWL), the replacing case corresponded to more serious wear condition than the rewelding case; the same work (either rewelding or replacing) of more labor hours corresponded to more serious wear condition than that of less labor hours; and the bolster horizontal wear liner was normally worn more seriously than the bolster vertical wear liner. Based on these three observations, one could easily find that, as shown by their names, the overall internal bolster wear conditions get more and more serious along with states from 1 (normal) to 3 (poor). Thus, such a choice set contained meaningful choices.

Figure 5.4. Categorization of Internal Truck Condition.



5.3.3. Other Variables

Finally, two more variables were included in the data set. One was the car number which was entered directly as a number. The other variable was the end of the car, which was entered 1 if the observation was the truck on the A end of the car and 2 if B end.

The names and definitions of the variables in the data set are summarized in table 5.2.

Table 5.2. Data Scheme in Data Set

Names	Description and definitions
car_no	the car number
car_end	**1** : the truck on A end of the car (simply, A truck) **2** : the truck on B end of the car (simply, B truck)
pwp_R(L)	pocket wear liners on the right (left) side of the truck. **1** : FINE (2 good, 2 OK, 2 present, etc.) **2** : PROBLEMATIC (1 good/1 worn, 1 OK/1 miss, etc.) **3** : POOR (2 worn out, 2 worn, 2 broken, etc.)
pow_R(L)	wear of pocket outer wall on the right side of the truck. 1 unit = 1/16 inch of wear.
rpl_R(L)	roof pedestal liners on the right (left) side of the car. **1** : FINE (2 OK, 2 new, 2 replaced, etc.) **2** : PROBLEMATIC (light worn, partly worn, 1 worn/1 OK, etc.) **3** : POOR (2 worn, 2 worn out, 2 miss, etc.)
int_exp	total expense on the repair for the internal parts of the bolster.
int_cate	states (categories) of the internal bolster condition state — description — BVWL — BHWP **1** — Normal — rw, hour 1 - 1.2 — rw or no need to repair **2** — bad — rw, hour 1 - 1.2 — rp, hour >= 0.2 **3** — poor — rp — anything

Notes : rw : reweld ; rp : replace;
BVWL : bolster vertical wear liner.
BHWP : bolster horizontal wear plate.

Chapter 6

A Case Study: Linear Model

As presented previously, one method of predictive inspection is to build a linear model between the total repair costs on the internal bolster parts and the external measurements. In this chapter, various linear models and the estimation results are presented. This is followed by an evaluation of the linear models.

6.1. Models and Results

The basic model specification is as shown in the equation (6.1.) and in table 6.1. Most of the external variables in data set were included in the models. The variables for pocket wall plates in problematic condition and for roof pedestal liner in problematic condition were excluded in order to keep the models estimable.

Table 6.1. Linear Model Specification.

Variables	Description	Expected Sign
Dependent		
int_exp	internal repair expense.	
Independent		
constant	constant term.	+
pwp_R_fn	dummy variable. 1, if pwp_R in fine condition (pwp_R=1); 0, otherwise.	-
pwp_R_pr	dummy variable. 1, if pwp_R in poor condition (pwp_R=3); 0, otherwise.	+
pow_ R	wear of pocket outer wall on the right side of the truck. 1 unit = 1/16 inches of wear.	+
rpl_ R _fn	dummy variable 1, if rpl_ R in fine condition (rpl_ L =1); 0, otherwise.	-
rpl_ R _pr	dummy variable 1, if rpl_R in poor condition (rpl_L =3); 0, otherwise.	+
pwp_L_fn	dummy variable. 1, if pwp_L in fine condition (pwp_L=1); 0, otherwise.	-
pwp_ L _pr	dummy variable. 1, if pwp_L in poor condition (pwp_L =3); 0, otherwise.	+
pow_ L	wear of pocket outer wall on the left side of the truck. 1 unit = 1/16 inches of wear.	+
rpl_ L _fn	dummy variable 1, if rpl_ L in fine condition (rpl_ L =1); 0, otherwise.	-
rpl_ L _pr	dummy variable 1, if rpl_L in poor condition (rpl_L =3); 0, otherwise.	+

$$
\begin{aligned}
\text{Internal repair cost } = \beta_0 &+ \beta_1 \cdot pwp\_R\_fn + \beta_2 \cdot pwp\_R\_pr \\
&+ \beta_3 \cdot pow\_R \quad + \beta_4 \cdot rpl\_R\_fn \\
&+ \beta_5 \cdot rpl\_R\_pr \ + \beta_6 \cdot pwp\_L\_fn \\
&+ \beta_7 \cdot pwp\_L\_pr + \beta_8 \cdot pow\_L \\
&+ \beta_9 \cdot rpl\_L\_fn \ + \beta_{10} \cdot rpl\_L\_pr + \varepsilon \ ,
\end{aligned} \qquad (6.1.)
$$

where β_0 was the constant, $\beta_1, \beta_2, \beta_3, \cdots \beta_{10}$ were the coefficients for external measurement variables, and ε was the random disturbance.

According to the prior knowledge of truck mechanics and maintenance, certain sign of the coefficients for the external variables could be expected as shown in table 4.3. The constant term was expected to be positive. This implied that even if all the other variables were zero, there would still be some repair cost incurred. For example, if no inspection was done to a truck or the inspection show good condition for all external variables, but for some reason the truck was sent to repair shop and disassembled, some labor and/or minor material costs would probably still be incurred since the car and truck were disassembled anyway. In general, the dummy variables for either pocket wall liners or roof pedestal liners being in fine condition, i.e. pwp_R_fn, pwp_L_fn, rpl_R_fn and rpl_L_fn, were expected to be negative or close to zero. The reason for this was simply that the repair cost would tend to decrease or at least not increase if the condition of the parts were fine. Conversely, the dummy variables for either pocket wall liners or roof pedestal liners being in poor condition, i.e. pwp_R_pr, pwp_L_ pr, rpl_R_ pr and rpl_L_ pr, were expected to be positive. The variables for pocket outer wall (pow_R and pow_L) were expected to be positive with the rationale that more repair should be done internally if more inches of wear on the pocket outer wall was observed.

The first estimation was based on the entire data set including the observations of both A end and B end trucks. The results of the estimation is summarized in table 6.2. It was observed that some of the signs of the estimated parameters were as expected and some others were not. Specifically, constant, rpl_R_pr, pow_L, and rpl_L_fn had both reasonable signs and relatively good t-statistics. The fit of the model, R-squared, 0.074, is very low.

Table 6.2. The Results from Linear Model Based on the Whole Data Set.

Dependent Variale : int_exp			
Independent Variable	**Estimated Coefficient**		**t-statistics**
constant	0.015	e	4.166
pwp_R_fn	18.285	u	0.969
pwp_R_pr	14.735	e	0.608
pow_R	-3.726	u	-0.52
rpl_R_fn	-6.796	e	-0.362
rpl_R_pr	19.711	e	1.053
pwp_L_fn	11.691	u	0.578
pwp_L_pr	13.378	e	0.49
pow_ L	8.895	e	1.177
rpl_ L _fn	-67.595	e	-3.119
rpl_ L _pr	-49.884	u	-2.197
R-squared : 0.074			

Notes: e : the sign of the estimated coefficient was as expected,

u : the sign of the estimated coefficient was not as expected.

Since the entire data set included the observations for both A end trucks and B end trucks, it was not unreasonable to suspect that there existed some difference between the true coefficients of external variables for A and B end trucks. Therefore, the same model was estimated on the data subsets of A and B end trucks separately. The results of the estimations are summarized in table 6.3. and table 6.4., respectively.

Several observations can be made concerning the results from the estimations on A end, B end data subsets and the entire data set. Most of the estimated coefficients were quite different from the estimation on A end truck subset to that on B subset. The signs of the last five estimated coefficients were the same for the estimations based on either A, B subset or the entire data set. The t-statistics of the estimated coefficients from the estimation on either subset were less significant than those from the entire data. In terms of fit of the model, it was obvious that both of the two separate models had larger values of R squared. Although the reduction of observations would cause the increase of the R-squared value, its impact should be negligible because of too large difference between the number of independent variables and number of observations in any of the three estimations. To test the previous suspection that the true coefficients were different between A and B subsets, a structural change test, or Chow test, was applied as follows,

$$F(13{,}201) = \frac{\left(\sum e_{A+B}^2 - \sum e_A^2 - \sum e_B^2\right)/11}{\left(\sum e_A^2 + \sum e_B^2\right)/(214-22)} = 0.43\,,$$

where $\sum e_A^2$, $\sum e_B^2$ and $\sum e_{A+B}^2$ were sum of squared residuals from the estimations based on A, B subsets and the entire data set, respectively. The value of F statistic 0.43 was much smaller than the tabled critical value of F test, 1.89, with the degree of freedom 11 and 192 (W. Greene, 1993). Therefore, we can not reject the null hypothesis that the true coefficients for A and B end truck subsets were the same. In other words, it is appropriate to rely on the estimation on the entire data set rather than on data subsets.

Table 6.3. The Results from Linear Model Based on A End Truck Subset.

Dependent Variale : int_exp			
Independent Variable	**Estimated Coefficient**		**t-statistics**
constant	0.017	e	5.216
pwp_R_fn	-0.358	e	-0.022
pwp_R_pr	19.634	e	0.932
pow_R	-5.6	u	-0.906
rpl_R_fn	-12.761	e	-0.795
rpl_R_pr	-1.117	u	-6.991
pwp_L_fn	7.412	u	0.461
pwp_L_pr	13.253	e	0.568
pow_ L	5.009	e	0.743
rpl_ L _fn	-50.212	e	-2.608
rpl_ L _pr	-20.562	u	-0.987
R-squared : 0.123			

Notes: e : the sign of the estimated coefficient was as expected,

u : the sign of the estimated coefficient was not as expected.

Table 6.4. The Results from Linear Model Based on B End Truck Subset

Dependent Variale : int_exp			
Independent Variable	**Estimated Coefficient**		**t-statistics**
constant	0.013	e	1.94
pwp_R_fn	36.390	u	1.02
pwp_R_pr	5.166	e	0.116
pow_R	1.947	e	0.142
rpl_R_fn	-9.933	e	-0.281
rpl_R_pr	35.656	e	1.024
pwp_L_fn	23.613	u	0.551
pwp_L_pr	25.288	e	0.489
pow_ L	7.375	e	0.529
rpl_ L _fn	-79.245	e	-2.014
rpl_ L _pr	-71.357	u	-1.769
R-squared : 0.09			

Notes: e : the sign of the estimated coefficient was as expected,

u : the sign of the estimated coefficient was not as expected.

6.2. Evaluation for the Linear Models.

Based on the data available for this research, the linear models provided fairly limited benefit for the prediction of the total repair cost on internal parts from external measurements. Several possible reasons may be raised.

Firstly, both external measurements and internal repair cost were somewhat subjectively and roughly identified. Externally, pocket wear liners and roof pedestal liners were measured in a purely qualitative manner, which would by nature introduce some subjectiveness. It was possible that the same condition may be judged as "OK" by one inspector but "good" by another, or "OK" some time but "good" the other time even by the same inspector. Additionally, the qualitative judgements force most of the external measurements to be defined as dummy variables in the model, and the only non-dummy variable, pocket outer wall, was valued also by several numbers ranging mostly from 1 to 5. Therefore, the independent variables were limited to a fairly small number of combinations of the values. This significantly reduced the quality of the linear models in a systematical way. Also, many internal cost data were repeated or around certain values. The reason for this was that both elements of internal repair cost , replaced materials and labor hours (hence labor charge), were not continously valued. Obviously, the prices of replaced parts are by nature discrete values. And the labor hours spent on internal repair were mostly artificially measured repeatedly at a few values. For example, most of the repair on bolster vertical wear liner took 1.1 hours and bolster horizontal wear liner either 0.2 or 0.32 hours. This seriously damaged the linear relationship between external measurements and internal repair cost since the same cost might correspond to several different external conditions.

Secondly, even if the aforementioned problem of subjectiveness and roughness of the data did not exist, some problems may lie in the overall formulation of the variables and data. Externally, it may not be adequate to use only the three measurements as independent variables. Some other important external variables may have been omitted from the inspection. For example, wedge rise may be another reasonable measurement for the external parts of the bolsters. Internally, it may not always be appropriate to infer the true internal condition from the information contained by the repair reports. For example, if the internal bolster condition was found to be fine after the car and truck were actually disassembled, some parts may still be replaced and some repairs be done because the car and truck were already disassembled and hence some costs were incurred anyway. One more specific example may be that many railroads replace the bolster center plate liners whenever the car is disassembled. In these cases, the information provided by the repair reports can not reflect the true internal condition. Therefore, there does not exist a significant relationship between the internal repair **cost** and external variables, even though it may be assumed that there does exist significant relationship between the true internal bolster **condition** and the external variables.

Chapter 7

A Case Study: Discrete Choice Model

As presented in previous chapters, one method of predictive inspection is, using discrete choice models, to build a nonlinear relationship between the states of internal truck condition and external measurements. In this chapter, a series of discrete choice models and the estimation results are presented first. This is followed by the presentation of the potential prediction with the model. Finally, the method is evaluated.

7.1. Models and Results

Beginning with a basic model specification, a series of three models (A, B, and C) were estimated. The results of each estimation were analyzed and led to the next one with certain changes of the specification. The final model specification (C) provided a relatively simple, practical and acceptable specification.

7.1.1. Model Specification A.

Following the previous theoretical presentation of discrete choice model and the description of the data set, it is natural to begin the model specification with all the possible independent variables as alternative specific variables and the three states of the internal bolster condition included. The model specification is shown in table 7.1.

Although an example discrete choice model specification for the context of freight car truck internal bolster condition has been presented previously, it is still useful here to explain the basic model specification in more detail. The first column of the table 7.1. contains the names of three states of internal bolster condition, i.e. "normal", "bad" and "poor". The first row of the table 7.1. contains the names of coefficients for the corresponding external measurement variables in the tendency function. The value in a cell of the table is the value of a variable corresponding to certain state (the first cell in the same row) and associated with a certain coefficient in the tendency function (the first cell in the same column). It needs to be emphasized that some variables in the specification did not actually exist in but were created from the data set during the modeling procedure and would show up in the estimation results.

To be more clear, the "normal" state of internal bolster condition in table 7.1. is taken as an example and several typical variables are explained in detail as follows. "β-constant_1" was the alternative-specific constant for the "normal" state (state 1). Therefore 1 was entered into the cell corresponding to the row of "normal" and column of "β-constant_1", and 0 into the cell corresponding to the rows of "bad" and "poor" and the column of "β-constant_1". "β-constant_2" was the alternative-specific constant for "bad" state. Therefore 0 was entered into the cell corresponding to the rows of "normal" and "poor" and the column of "β-constant_2", and 1 into the cell corresponding to the row of "bad" and the column of "β-constant_2". The same rationale was applicable to all the other alternative-specific variables. The coefficient "β-pwpRfn_1" corresponded to a variable "pwpRfn_1", which was an alternative-specific variable for "normal" state. The variable was assigned 1 if the pocket wear plates in the right side of the truck were in "fine"

Table 7.1. Discrete Choice Model Specific A

Tendency of being in the state:	β-*constant_1*	β-*constant_2*	β-*pwpRfn_1*	β-*pwpRfn_2*	β-*pwpRpb_1*	β-*pwpRpb_2*	β-*powR_1*	β-*powR_2*
1, normal	1	0	1 if pwp_R fine; 0 otherwise	0	1 if pwp_R problematic; 0 otherwise	0	pow_R	0
2, bad	0	1	0	1 if pwp_R fine; 0 otherwise	0	1 if pwp_R problematic; 0 otherwise	0	pow_R
3, poor	0	0	0	0	0	0	0	0

	β-*rplRfn_1*	β-*rplRfn_2*	β-*rplRpb_1*	β-*rplRpb_2*	β-*pwpLfn_1*	β-*pwpLfn_2*	β-*pwpLpb_1*	β-*pwpLpb_2*
1, normal	1 if rpl_R fine; 0 otherwise	0	1 if rpl_R problematic; 0 otherwise	0	1 if pwp_L fine; 0 otherwise	0	1 if pwp_L problematic; 0 otherwise	0
2, bad	0	1 if rpl_R fine; 0 otherwise	0	1 if rpl_R problematic; 0 otherwise	0	1 if pwp_L fine ; 0 otherwise	0	1 if pwp_L problematic; 0 otherwise
3, poor	0	0	0	0	0	0	0	0

	β-*powL_1*	β-*powL_2*	β-*rplLfn_1*	β-*rplLfn_2*	β-*rplLpb_1*	β-*rplLpb_2*		
1, normal	pow_L	0	1 if rpl_L fine; 0 otherwise	0	1 if rpl_L problematic; 0 otherwise	0		
2, bad	0	pow_L	0	1 if rpl_L fine; 0 otherwise	0	1 if rpl_L problematic; 0 otherwise		
3, poor	0	0	0	0	0	0		

condition and 0 otherwise. Put in other words, the variable "pwpRfn_1" was assigned 1 if the variable "pwp_R" in the data set was 1 (see section 5.2.3. and table 5.2.), and 0 otherwise. Notice that the variable "pwp_R" is a different variable from "pwpRfn_1". The former was the actual external measurement in the data set and the latter created in the modeling procedure. One could see that the variable "pwpRfn_1" was named so because "pwpR" corresponded to "pwp_R" (pocket wear plates in the right side of the truck), "fn" corresponded to the "fine" condition for "pwp_R", and "_1" implied specific for "normal" state. Similarly, the coefficient "β-powR_1" corresponded to the variable "powR_1", which was specific for "normal" state. It was assigned to simply be the value of the variable "pow_R" in the data set since "pow_R" was a numerical instead of dummy variable. The remaining variables are similar to one of the above cases.

Notice that 0's were entered into all the cells in the row of "poor" state. In other words, all the variables and constants for the "poor" state were assigned 0's. The reason for this is that discrete choice models estimate the parameters based on the difference between the tendencies of different states. Therefore, one state must be chosen to be the base state, and the difference between the other states and this base state will be actually used for the estimation. The variables and constants of the base state are assigned to be 0's and so the products of the estimated coefficients and values of the variables for the other states will be the differences between the other and base states. In the case of this study, "poor" state was chosen as the base state, so 0's were entered to all the cells in the row of "poor" state. For example, the first column of table 7.1. corresponds to the alternative-specific constant for the "normal" state. Zero was entered into the second and third row in the first column. Therefore, the estimated constant "β-constant_1" (more generally, the product of "β-constant_1" and 1) will be the difference between the alternative specific constants for "normal" state and that for "poor" state which is 0. The similar rationale can be applied to the other variables and constants.

The model was specified such that the signs of some parameters can be expected according to prior knowledge and some others are ambiguous. For example, the coefficient of the variable "pwpRfn_1" was expected to be positive. This implies that the tendency of internal bolster condition being in "normal" state would increase if the pocket wear plates are in "fine" condition. For another example, the sign of the coefficient of the variable "pwpRfn_2" was ambiguous because this coefficient is supposed to reflect the impact to (either increase or decrease) the tendency of being in "bad" state relative to "poor" state if the pocket wear plates are in "fine" condition.

The estimation results of the specification A are shown in table 7.2. Some estimated coefficients have signs as expected according to our prior knowledge and some others do not. For example, the estimated coefficient for "pwpRfn_1" was not as expected to be positive. This implied that the tendency of bolster internal condition being in "normal" state would decrease if the pocket wear plates were in "fine" condition. This was not consistent with our prior knowledge. For another example, the estimated coefficient for "rplRfn_1" was positive as expected. This implied that the tendency of bolster internal condition being in "normal" state would increase if the roof pedestal liners were in "fine" state. This was consistent with our prior knowledge.

Several statistics for the model are summarized in table 7.2. Goodness of fit is the equivalent statistic to the determinant coefficient, or R squared, in linear regression. It measures the portion of the original variance of the dependent variable explained by the model. Another measure is "percent correctly predicted". This statistic is defined as the portion of the observations whose actual internal condition state corresponds to the state with the highest probability obtained from the model estimation. For example, if, out of a sample of 100 trucks, the actual internal states of 60 trucks are the same as the states to which the model assigns the highest probability, then the percent correctly predicted is 60%.

Up to now, all the previous discrete choice modeling proceeded with the assumption that all the observations involved the same systematic characteristics and there was no structural difference among observations. Specifically, this implied that the true coefficients of the variables were the same across the observations of the trucks. This was not necessarily true because there were indeed some differences across the observations. As mentioned early, the external measurement data were based on two (1990 and 1992) different versions of the inspection reports, whose formats changed totally and content slightly. In addition, one half of the observations were A end trucks and the other half B end trucks. Model specification B was targeted towards possible structural change introduced by these two cases.

Table 7.2. The Estimation Results from Discrete Choice Model A

Independent Variable	Estimated Coefficient	t-statistic
constant_1	0.590	0.538
constant_2	0.288	0.300
pwpRfn_1	-0.807	-1.192
pwpRfn_2	0.153	0.249
pwpRpb_1	-0.233	-0.303
pwpRpb_2	0.315	0.445
powR_1	0.135	0.577
powR_2	-0.010	-0.05
rplRfn_1	0.053	0.083
rplRfn_2	0.417	0.774
rplRpb_1	0.342	0.528
rplRpb_2	0.674	1.237
pwpLfn_1	0.623	0.844
pwpLfn_2	0.586	0.939
pwpLpb_1	1.079	1.224
pwpLpb_2	0.992	1.33
powL_1	-0.462	-1.839
powL_2	-0.220	-1.005
rplLfn_1	1.174	1.937
rplLfn_2	0.893	1.659
rplLpb_1	-1.588	-1.716
rplLpb_2	-0.044	-0.077
Summary statistics		
log likelihood at convergence	-158.56	
log likelihood initial	-191.16	
goodness of fit	0.171	
number of observations	174	
percent correctly predicted	60.01	

7.1.2. Model Specification B

To capture the possible influence introduced by the difference between the versions of inspection reports, dummy variables for the different inspection version, “data90_1” and "data90_2" were added into the model specified as shown in table 7.3. The results of the estimation is shown in the block of “Model on the entire data set” in table 7.4. It was observed that only the variable specific for “bad” state, “data90_2”, had a t-statistic larger than 1. This suggests that the change of inspection report format did not introduce significant structural change.

Table 7.3. Specification for Dummy Variables Added for the Different Inspection Report Formats

Tendency of being in the state:	β-data90_1	β-data90_2
1. Normal	1 if inspection 90 version; 0 otherwise	0
2. Bad	0	1 if inspection 90 version; 0 otherwise
3. Poor	0	0

To determine whether the coefficients were different for the A and B end truck subsets, the same model specification was further estimated on the two subsets, respectively. For the purpose of comparison, the estimation results are shown in table 7.4., along with that from the estimation on the entire data set.

It was observed that the estimation using either A or B end truck subset produced better fit of the model than the estimation using the entire data set. This may not necessarily imply that the two subset estimations are more reasonable and hence the true coefficients for A and B subsets are different systematically. The reason may be that one half of all the observations were used in the estimations on the subsets to estimate the same number of variables as in the estimation on the entire data set. This would normally

Table 7.4. Estimation Results from Model Specification B.

Independent variables	Model on the whole data set		Model on the A subset		Model on the B subset	
	Estimated coef.	t-statistics	Estimated coef.	t-statistics	Estimated coef.	t-statistics
constant_1	0.606	0.534	-2.419	-1.282	2.494	1.478
constant_2	0.314	0.315	-1.683	-1.040	1.265	0.832
data90_1	-0.040	-0.053	0.123	0.113	0.558	0.426
data90_2	-0.664	-1.020	-0.274	-0.307	-0.465	-0.434
pwpRfn_1	-0.759	-1.105	1.038	0.889	-2.310	-2.114
pwpRfn_2	0.231	0.369	0.222	0.243	0.337	0.348
pwpRpb_1	-0.252	-0.323	0.812	0.624	-0.811	-0.650
pwpRpb_2	0.394	0.549	-0.313	-0.303	1.273	1.121
powR_1	0.204	0.829	0.886	2.129	-0.319	-0.773
powR_2	0.061	0.295	0.425	1.201	-0.188	-0.587
rplRfn_1	0.028	0.044	0.980	1.045	-0.042	-0.040
rplRfn_2	0.368	0.677	0.764	0.974	0.579	0.658
rplRpb_1	0.290	0.440	0.774	0.691	-0.145	-0.146
rplRpb_2	0.781	1.409	0.776	0.919	0.842	1.000
pwpLfn_1	0.621	0.767	-0.449	-0.361	1.753	1.330
pwpLfn_2	0.876	1.278	1.343	1.300	0.567	0.525
pwpLpb_1	1.105	1.175	1.162	0.799	1.671	1.099
pwpLpb_2	1.310	1.621	2.425	1.977	0.649	0.544
powL_1	-0.513	-1.882	-0.595	-1.408	-0.554	-1.312
powL_2	-0.223	-0.960	-0.201	-0.567	-0.238	-0.624
rplLfn_1	1.196	1.947	2.060	2.164	0.035	0.035
rplLfn_2	0.904	1.666	1.141	1.709	0.419	0.470
rplLpb_1	-1.687	-1.772	-10.514	-0.145	-1.364	-1.146
rplLpb_2	-0.030	-0.051	0.177	0.197	-0.564	-0.642
Summary statistics						
log likelihood at convergence	-157.58		-73.307		-71.945	
log likelihood initial	-191.16		-95.579		-95.579	
likelihood ratio statistic	0.176		0.233		0.247	
number of observations	174		87		87	
percent correctly predicted	59.195		50.575		68.966	

Table 7.5. Estimation Results for Model Specification C.

Independent Variable	Estimated Coefficient	t-statistics
constant_1	0.555	0.486
constant_2	0.346	0.348
data90_2	-0.298	-0.644
pwpRfn_1	-0.769	-1.129
pwpRfn_2	0.176	0.285
pwpRpb_1	-0.233	-0.302
pwpRpb_2	0.343	0.481
powR_1	0.191	0.794
powR_2	0.028	0.137
rplRfn_1	0.048	0.076
rplRfn_2	0.426	0.794
rplRpb_1	0.314	0.484
rplRpb_2	0.720	1.309
pwpLfn_1	0.653	0.880
pwpLfn_2	0.745	1.119
pwpLpb_1	1.105	1.245
pwpLpb_2	1.172	1.479
powL_1	-0.507	-1.876
powL_2	-0.248	-1.071
rplLfn_1	1.187	1.951
rplLfn_2	0.897	1.666
rplLpb_1	-1.635	-1.748
rplLpb_2	-0.066	-0.114
Summary statistics		
log likelihood at convergence	-158.3	
log likelihood initial	-191.16	
goodness of fit	0.176	
number of observations	174	
percent correctly predicted	56.897	

increase the goodness of fit by the nature of statistical inference. To actually determine whether there existed any structural change between A and B subsets, a likelihood ratio test was employed as follows:

$$\chi^2_{24} = (157.58 - 73.307 - 71.945)*2 = 24.656,$$

which was smaller than the critical value of chi-squared distribution, 36.42, with 24 degree of freedom and 0.05 level of significance (Greene, 1993). This implies that the null hypothesis that the true parameters for A and B subsets were the same can not be rejected. Therefore it is appropriate to rely on the estimation using the entire data set.

7.1.3. Model Specification C

In the model estimation B based on the entire data set, it was observed that the variable, "data90_1", had a very low t-statistic associated with the estimated coefficients. Therefore, model specification C was estimated with this variable removed away from the model specification B with the rationale that the variable was not significantly related to the internal bolster states. The estimation results are shown in table 7.5. The goodness of fit was 0.176, and 56.897 percent of the sample were correctly predicted.

Relatively speaking, the model specification C was considered an acceptable and practically useful model. It was used for the demonstration of the prediction of the internal bolster condition in the next section.

7.2. Prediction of the Internal Truck Condition

The ultimate goal of the new inspection technique is to provide a way to predict the internal bolster condition. The predicted internal truck condition can be in turn used to form more cost-effective maintenance decision. More specifically, it will predict the probability of internal bolster condition being in certain pre-defined state given the corresponding external measurements. By combining the probabilities with the costs associated with different maintenance decisions, one can make more a cost-effective and reliable decision. In this section, this prediction procedure is demonstrated. Then, using the data set for the research, the prediction ability of model specification C is demonstrated.

7.2.1. Predicting the Probability

First, following the concepts of discrete choice model, we can simply obtain the prediction of the probabilities that a truck's internal bolster condition will be in certain state if we have the external measurement variables of the truck observed. Given the external variables of a truck inspected and the coefficients estimated from the model specification C, the tendencies and hence the exponential value of the tendencies for each internal state can be determined. Then the probability of each state can be obtained following equation (4.10.).

As shown in table 7.6., the A end truck of car 1350 is given as an example for this prediction procedure. In the last three columns of the table, the values of the variables in the model specification were entered according to the actual external measurement variables "pwp_R=1(fine)", "pow_R=3", "rpl_R=1(fine)", "pwp_L=1(fine)", "pow_L=3" and "rpl_L=1(fine)". The coefficients estimated from the model specification C are given in the second column of the table. The tendency for each state is simply the summation of the products of the estimated coefficients and the corresponding variables for that state. For example, the tendency of "normal" state is given by

$$0.555\cdot 1-0.769\cdot 1+0.191\cdot 3+0.048\cdot 1+0.653\cdot 1-0.507\cdot 3+1.187\cdot 1=0.726\ .$$

Similarly, the tendencies of "bad" and "poor" states are 1.93 and 0. Then the exponential values of the tendency of "normal" state is given by

$$\exp(0.726)=2.067\,.$$

Similarly, exponential values of "bad" and "poor" states are 6.89 and 1. Finally, the probability of internal bolster condition being in "normal" state can be predicted by

$$\Pr ob(Normal) = \frac{2.067}{2.067 + 1.93 + 1} = 0.208.$$

Similarly, it can be predicted that the internal bolster condition would be in "bad" and "poor" states with the probabilities of 0.692 and 0.1, respectively.

Table 7.6. Demonstration of the Prediction of the Probabilities of Internal Bolster Condition for A end Truck of Car 1350

Independent	**Estimated**	**Value of the variables**		
		Normal (1)	**Bad (2)**	**Poor (3)**
constant_1	0.555	1	0	0
constant_2	0.346	0	1	0
data90_2	-0.298	0	0	0
pwpRfn_1	-0.769	1	0	0
pwpRfn_2	0.176	0	1	0
pwpRpb_1	-0.233	0	0	0
pwpRpb_2	0.343	0	0	0
powR_1	0.191	3	0	0
powR_2	0.028	0	3	0
rplRfn_1	0.048	1	0	0
rplRfn_2	0.426	0	1	0
rplRpb_1	0.314	0	0	0
rplRpb_2	0.720	0	0	0
pwpLfn_1	0.653	1	0	0
pwpLfn_2	0.745	0	1	0
pwpLpb_1	1.105	0	0	0
pwpLpb_2	1.172	0	0	0
powL_1	-0.507	3	0	0
powL_2	-0.248	0	3	0
rplLfn_1	1.187	1	0	0
rplLfn_2	0.897	0	1	0
rplLpb_1	-1.635	0	0	0
rplLpb_2	-0.066	0	0	0
Tendencies		**0.726**	**1.93**	**0**
Exp(tendencies)		**2.067**	**6.890**	**1**
Predicted probabilities		**0.208**	**0.692**	**0.1**

7.2.2. Maintenance Decision Making

Once the probabilities of the states are predicted, the next question must be what maintenance decision should be made to the truck, e.g., sending it to repair or keep it running for some more time. With the costs associated with the states and decisions known, a more effective decision may be made. This is illustrated by the following example.

Suppose the internal condition of the A end truck of car 1350 is predicted as above. For the practical and simplistic purpose, we combine the state "bad" and "poor" into a single state "**abnormal**" and therefore we ended up with two states, "**normal**" and "**abnormal**". It is easy to know the probability for the truck's internal condition being in "normal" and "abnormal" states are **0.208** (see table 7.6.) and **0.792** (1 - 0.208). Suppose the following two costs are known. One is false-alarm cost, which is incurred when the truck's internal condition is considered **abnormal** and so it is decided to be sent for repair, but it is found in **acceptable** condition after actually disassembling the car and truck in repair shop. The other cost is missing-failure cost, which is incurred when the truck's internal condition is considered **normal** and so it is decided to be kept in operation, but it is actually in **abnormal** condition. Denote false-alarm cost and missing-failure cost by c_1 and c_2, respectively. It is obviously that a cost-effective decision can be made as follows:

Send the truck to repair if $0 \cdot 208 \cdot c_1 \leq 0.792 \cdot c_2$;

Keep the truck operating otherwise.

Note that the above discussion is targeted toward every single truck. But in practice the inspection and repair are conducted by each car including two trucks instead of by each truck. Therefore it is more practically useful to predict the probability that **at least one truck** of a car has its internal bolster condition being in "abnormal" condition. Following the same procedure for the A end truck of car 1350 illustrated in table 7.6., for the B end truck, the probabilities of its internal truck condition being in "normal" and "abnormal" states can be predicted as 0.293, and 0.707 respectively. Therefore, the probabilities of "normal" and "abnormal" states for A end and B end trucks of car. 1350 are 0.208 and 0.792, and 0.293 and 0.707, respectively. Under the assumption that the internal condition of the two trucks of the same car are not correlated each other, the joint probabilities of the two trucks' internal bolster condition are simply the product of the marginal probabilities for each truck. For example, the probability of the internal bolster condition of the two trucks both being normal is given by $0.208 \cdot 0.293 = \mathbf{0.06}$. Obviously, the probability of at least one trucks' internal bolster condition being in abnormal state is given by $1 - 0.06 = \mathbf{0.94}$. (The joint probabilities are shown in table 7.7.). Similarly, if the false-alarm and missing-failure costs in this case are C_1 and C_2, then a cost-effective decision can be made as follows:

Send the car repair if $0.06 \cdot C_1 \leq 0.94 \cdot C_2$*;*

Keep the car operating otherwise.

It needs to be mentioned that the costs here should be comprehensively defined in that it contains many different types of the costs, e.g. direct repair cost, potential cost from possible accident, etc.

Table 7.7. Joint Probabilities of the Two Trucks' Internal Condition of the Same Car.

	A end truck	
B end truck	Normal	Abnormal
Normal	0.061	0.232
Abnormal	0.147	0.560

In some practices, the repair facility is congested even though the above manintenance decision procedure is applied. In this case, further maintenance criterion must be considered. A reasonable strategy may be limit the repair to only those cars whose internal condition is highly likely to be in "abnormal" state. For example, if two trucks are both justified to be repaired according to the maintenance decision strategy previously, but only one truck can be repaired by the repair facility available, then a reasonable maintenance decision may further be

> *Send the truck whose probability of internal condition being in "abnormal" state is higher.*

7.2.3. Prediction Ability

To demonstrate the prediction ability of the model specification C, the sample set was first divided into two parts. The first part contains 150 observations and second the remaining 24. This was done such that the structure of true internal state is the same for these two parts, meaning that the proportion of each state is the same in the two parts. Then, the model specification C was estimated using the 150 observations in the first part and the estimated results were used to predict the internal condition of the remaining 24 observations. The prediction was considered proper because of the same structure of the two parts of sample. The results of the estimation based on the first 150 observations are shown in table 7.8. and the prediction for the remaining 24 observations is shown in table 7.9. The true internal states are presented in the first column of table 7.9. The second column includes the predicted states which are the states corresponding to the largest probabilities obtained from the model estimation. The detail of the prediction for each truck are presented in the last several columns. For example, for the truck 1, the internal state was predicted to be "bad" while it was actually "normal".

In practice, more concerns are put on the trucks in "bad" or "poor" states than those in "good". Therefore, it is more important to know the structure of correctly predicted percent, meaning the percent correctly predicted for the observations grouped by each internal state, than that of all the sample as a whole.The percentage correctly predicted for the trucks truly in "normal", "bad" and "poor" internal states were 33.33%, 69.23% and 0%, respectively. Although this result does not appear to be so acceptable, further analysis in chapter 8 about the percent correctly predicted will show the appealing aspects of the results.

Table 7.8. The Results of Estimation Based on the First 150 Observations

Independent Variables	Estimated Coefficient	t-statistics
constant_1	-0.061	-0.051
constant_2	-0.301	-0.278
data90_2	-0.282	-0.546
pwpRfn_1	-0.815	-1.168
pwpRfn_2	0.340	0.521
pwpRpb_1	0.282	0.339
pwpRpb_2	1.063	1.330
powR_1	0.239	0.931
powR_2	-0.064	-0.291
rplRfn_1	0.098	0.146
rplRfn_2	0.671	1.142
rplRpb_1	0.291	0.412
rplRpb_2	0.709	1.142
pwpLfn_1	0.527	0.675
pwpLfn_2	0.588	0.798
pwpLpb_1	1.588	1.562
pwpLpb_2	1.806	1.888
powL_1	-0.373	-1.294
powL_2	-0.19	-0.431
rplLfn_1	1.262	1.900
rplLfn_2	1.122	1.901
rplLpb_1	-1.069	-1.088
rplLpb_2	0.414	0.608
Summary statistics		
log likelihood at convergence	-133.6	
log likelihood initial	-164.79	
goodness of fit	0.189	
number of observations	150	
percent correctly predicted	58.667	

Table 7.9. The Prediction for the Remaining 24 Observations Using the Estimation Result Based on the First 150 Observations

Observation	True	Predicted State	Normal (1)	Bad (2)	Poor (3)
1	1	2	w (N->B)		
2	2	2		r	
3	2	2		r	
4	2	2		r	
5	1	1	r		
6	2	2		r	
7	2	1		w (B->N)	
8	2	1		w (B->N)	
9	2	2		r	
10	2	2		r	
11	2	2		r	
12	2	1		w (B->N)	
13	2	2		r	
14	1	2	w (N->B)		
15	1	2	w (N->B)		
16	1	1	r		
17	1	2	w (N>B)		
18	3	2		r	w (P->B)
19	3	2			w (P->B)
20	3	2			w (P->B)
21	3	2			w (P->B)
22	2	3		w (B->P)	
23	3	2			w (P->B)
24	2	2		r	
Percent Correctly Predicted			33.33%	69.23%	0%

Note: 1). w (N->B): wrong prediction to be "bad" while it is actually "normal".

2). w (B->N): wrong prediction to be "normal" while it is actually "bad".

3). w (P->B): wrong prediction to be "bad" while it is actually "poor".

4). w (P->N): wrong prediction to be "bad" while it is actually "poor".

5). r: right prediction.

7.3. Evaluation for the Discrete Choice Models.

Based on the data available for the research, the results of the choice models provide important information and the value for further research along the direction. As is common in the discrete choice models in many different contexts, the goodness of fit of the previous models ranged from 0.15 to 0.2.

Comparing the discrete choice models with linear models applied previously, the following observations could be made. Statistically, choice models were better than linear models in that better goodness of fit was provided by the choice models. The reason for this may be that the relationship that choice models were supposed to capture was more proper than the relationship that the linear models were. First, internal bolster condition is probably more directly related to the external measurements, while the repair cost on the internal bolster parts might include some elements which are not significantly related to the external condition. Second, even if the repair cost on the internal bolster parts contained no insignificant elements, the linear models may still be problematic. The reason for this was that the repair cost took the same values repeatedly since its two elements, labor hours and material price, are by nature discrete values. But linear models are intended to capture the linear relationship between continuous variables. Therefore it is probably more appropriate to have models based on the assumption of the internal condition represented as discrete states than to have it as continuous value.

As mentioned previously, a weakness of discrete choice model is the lack of strong supportive underlying behavioral theory. The internal truck condition are essentially not discrete alternatives, but a continuous variable or practically ordinal discrete levels. This weakness will be addressed by the performance threshold models presented in the next chapter.

Chapter 8

A Case Study: Performance Threshold Method

As presented previously, an alternative method of predictive inspection is the performance threshold method. In this chapter, a series of performance threshold models and the estimation results are presented. This is followed by the demonstration of the prediction for the internal truck condition using the model. Finally, the method is evaluated in comparison with discrete choice method.

8.1. Models and Results

A model calibrated using the entire data set was estimated first, and then the same model specification was estimated using the A end and B end data subsets in order to test whether structural change was involved.

8.1.1. Model Based on the Entire Data Set

As presented previously, the performance threshold method assumed that the performance the truck internal area is a linear function of external measurement variables plus a random disturbance term, and that a series of thresholds of performance produce several ordinal intervals of performance each of which corresponds to an internal truck condition or state. The performance threshold method seeks to estimate the parameters in the linear function of external measurement variables and the thresholds.

A model was specified as shown in Table 8.1. and estimated using the entire data set. The underlying performance function is given by

$$
\begin{aligned}
P = \alpha_0 + \alpha_1 \cdot data90 + \alpha_2 \cdot pwp\_R\_fn + \alpha_3 \cdot pwp\_R\_pr + \alpha_4 \cdot pow\_R \\
+ \alpha_5 \cdot rpl\_R\_fn + \alpha_6 \cdot rpl\_R\_pr \\
+ \alpha_7 \cdot pwp\_L\_fn + \alpha_8 \cdot pwp\_L\_pr + \alpha_9 \cdot pow\_L \\
+ \alpha_{10} \cdot rpl\_L\_fn + \alpha_{11} \cdot rpl\_L\_pr,
\end{aligned}
\tag{8.1}
$$

where P is the underlying performance, and α_0, α_1, α_1, $\alpha_2 \cdots \alpha_{11}$ are parameters to be estimated.

The sign of the most of the estimated parameters can be expected according to prior knowledge. All the coefficients for the dummy variables for external measurement being in "fine" condition, *"pwp_R_fn", "rpl_R_fn", "pwp_L_fn" and "rpl_L_fn"* were expected to be negative. This implies that if an external measurement is in "fine" condition, then the performance value of truck internal area decreases towards the "normal" condition since "normal", "bad" and "poor" states were ranked increasingly 1, 2, and 3, respectively. Conversely, the coefficients for the dummy variables for external measurement being in "poor" condition, *"pwp_R_pr", "rpl_R_pr", "pwp_L_pr"* and *"rpl_L_pr"* were expected to be positive. For the variables "*pow_R*" and "*pow_L*", the signs of their coefficients were expected to be positive. This implies that the more wear on pocket outer wall, the higher the performance value and the more the internal condition tends towards problematic or poor states. The expectation of the estimated coefficients are shown in Table 8.1. The sign of the constant term and the coefficient for dummy variable, *data*90, is ambiguous.

The estimation results of the model are shown in Table 8.2. Some estimated coefficients have signs as expected and some others do not. For example, the estimated

Table 8.1. The Performance Threshold Model Specification Using the Entire Data Set

Variables	Description	Expected Sign
Dependent		
int_cate	ordinal state of internal truck condition. (1="Good", 2="bad", 3="poor")	
Independent		
constant	Constant Term	ambiguous
data90	dummy variable. 1, if the external inspection data is in 1990 format; 0,otherwise.	ambiguous
pwp_R_fn	dummy variable. 1, if pwp_R in fine condition (pwp_R=1); 0, otherwise.	-
pwp_R_pr	dummy variable. 1, if pwp_R in poor condition (pwp_R=4); 0, otherwise.	+
pow_ R	wear of pocket outer wall on the right side of the truck. 1 unit = 1/16 inches of wear.	+
rpl_ R _fn	dummy variable 1, if rpl_ R in fine condition (rpl_ L =1); 0, otherwise.	-
rpl_ R _pr	dummy variable 1, if rpl_R in poor condition (rpl_L =4); 0, otherwise.	+
pwp_L_fn	dummy variable. 1, if pwp_L in fine condition (pwp_L=1); 0, otherwise.	-
pwp_ L _pr	dummy variable. 1, if pwp_L in poor condition (pwp_L =4); 0, otherwise.	+
pow_ L	wear of pocket outer wall on the left side of the truck. 1 unit = 1/16 inches of wear.	+
rpl_ L _fn	dummy variable 1, if rpl_ L in fine condition (rpl_ L =1); 0, otherwise.	-
rpl_ L _pr	dummy variable 1, if rpl_L in poor condition (rpl_L =4); 0, otherwise.	+

coefficient for the variable "*pwp_R_fn*" is positive, not as expected, while the coefficient for the variable "*rpl_R_pr*" is positive as expected. The estimated threshold,1.664, is also shown in the table. Since the first threshold is set to be 0, only the second one, 1.664, is shown in the Table. This implies that the truck internal condition would be considered in "normal" state if the performance value of a truck's internal area is less than 0, "bad" if the performance value falls in the interval (0, 1.664) and "poor" if larger than 1.664. Several statistics for the model are also summarized. Goodness of fit of the model is 0.185, which is slightly higher than that of discrete choice model specification C in chapter 7. The percent correctly predicted is 57.471%. In performance threshold method, percent correctly predicted is defined as the portion of the observations whose actual internal states correspond to the predicted state. The predicted state is the state whose corresponding threshold interval the performance value falls into. For example, if, out of a sample of 100 trucks, the actual internal states of 60 trucks are the same as the states whose corresponding threshold interval contains the performance values of these 60 trucks which are estimated from the model, then the percent correctly predicted is 60%.

8.1.2. Structural Change

Similar to the previous discussion for discrete choice method, it was tested whether any structural change existed for A end and B end data subsets. The model specification shown in Table 8.1. was estimated using the two data subsets, respectively. The results are shown in Table 8.3. along with the results from the estimation using the entire data set for the purpose of comparison.

To determine whether there exists any structural change between A end and B end data subsets, a likelihood ration test was employed as follows:

$$\chi^2_{(11)} = 2(161.98 - 77.686 - 76.607)=7.687,$$

which is smaller than the critical value of chi-squared, 21.03, with 12 degrees of freedom and 0.05 level of significance (Greene, 1993). This implies that the null hypothesis that the

Table 8.2. The Estimation Results of the Performance Threshold Model Using the Entire Data Set

Dependent Variable : int_exp		
Independent Variable	**Estimated Coefficient**	**t-statistics**
constant	0.868	1.802
data90	-0.267	-1.052
pwp_R_fn	0.202	0.920
pwp_R_pr	-0.144	-0.511
pow_R	-0.046	-0.524
rpl_R_fn	0.050	0.218
rpl_R_pr	0.094	0.410
pwp_L_fn	0.140	0.584
pwp_L_pr	0.308	0.882
pow_ L	0.170	1.836
rpl_ L _fn	-0.810	-3.005
rpl_ L _pr	-0.405	-1.472
threshold 2	1.664	11.924
Summary Statistics		
log likelihood at convergence	-161.98	
log likelihood initial	-198.86	
number of observations	174	
goodness of fit	0.185	
percent correctly predicted	57.471	

Table 8.3. Estimation Results Using the Entire Data Set, A end and B end Subsets.

Independent Variables	Model on the entire data set		Model on the A subset		Model on the B subset	
	Estimated coef.	**t-statistics**	**Estimated coef.**	**t-statistics**	**Estimated coef.**	**t-statistics**
constant	0.868	1.802	1.824	2.340	0.297	0.430
data90	-0.267	-1.052	-0.393	-1.096	-0.071	-0.182
pwp_R_fn	0.202	0.920	-0.105	-0.320	0.485	1.511
pwp_R_pb	-0.144	-0.511	0.281	0.643	-0.546	-1.379
pow_R	-0.046	-0.524	-0.262	-1.962	0.069	0.541
rpl_R_fn	0.050	0.218	-0.164	-0.481	0.023	0.070
rpl_R_pb	0.094	0.410	0.172	0.501	-0.010	-0.031
pwp_L_fn	0.140	0.584	0.451	1.389	-0.015	-0.039
pwp_L_pb	0.308	0.882	0.237	1.463	0.652	1.242
pow_ L	0.170	1.836	0.168	1.188	0.169	1.255
rpl_ L _fn	-0.810	-3.005	-1.298	-3.233	-0.469	-1.195
rpl_ L _pb	-0.405	-1.472	-0.582	-1.398	-0.450	-1.135
threshold 2	1.664	11.924	1.739	8.035	1.796	8.547
Summary statistics						
log likelihood at convergence	-161.98		-77.686		-76.607	
log likelihood initial	-198.86		101.29		-97.417	
number of observations	174		87		87	
goodness of fit	0.185		0.233		0.214	
percent correctly predicted	57.471		50.575		64.368	

true parameters for A and B end data subsets are the same can not be rejected. Therefore it is appropriate to rely on the estimation based on the entire data set.

8.2. Prediction

8.2.1. Prediction and Maintenance Decision

With the parameters and thresholds estimated, the internal condition for a truck can be predicted once its external measurements variables are observed. Specifically, the underlying performance value of the truck can be first obtained by inserting the external variables into the estimated performance function. Then, by comparing the performance value to the threshold intervals, the internal condition can be predicted to be in the state whose corresponding threshold interval contains the calculated performance value. The following example illustrates this procedure.

Suppose the parameters and thresholds are estimated as shown in Table 8.2. and a truck's external measurements are observed as follows: 1990 format of inspection, "pwp_R = 1 (fine)", "pow_R = 2 (2/16 inches of wear)", "rpl_R = 1 (fine)", "pwp_L = 1 (fine)", "pow_L = 2 (2/16 inches of wear)" and "rpl_L = 1 (fine)". The prediction of the internal condition is demonstrated in Table 8.4. The above external measurements can be translated into the values of the variables as shown in the second columns of Table 8.2. Transferred from Table 8.2., estimated coefficients are presented in the third column. The products of the value of variables and estimated coefficients are entered into the fourth column, which in turn are summed to the value of estimated performance function, 0.43. Since the two thresholds are 0 and 1.664, three performance intervals corresponding to three states are: "normal" if performance value <= 0, "bad" if 0 < performance value < 1.664, and "poor" if performance value >= 1.664. Therefore, the internal condition state can be predicted as in "bad" state since the estimated performance value 0.43 falls in the interval (0, 1.664).

Table 8.4. Demonstration of the Prediction for Internal Truck Condition By the Performance Threshold Model

Independent Variable	**Value of the Variables**	**Estimated Coefficients**	**Variables * Coefficients**
constant	1	0.868	1.802
data90	1	-0.267	-1.052
pwp_R_fn	1	0.202	0.920
pwp_R_pr	0	-0.144	-0.511
pow_R	2	-0.046	-0.524
rpl_R_fn	1	0.050	0.218
rpl_R_pr	0	0.094	0.410
pwp_L_fn	1	0.140	0.584
pwp_L_pr	0	0.308	0.882
pow_ L	2	0.170	1.836
rpl_ L _fn	1	-0.810	-3.005
rpl_ L _pr	0	-0.405	-1.472
Estimated Value of Performance Function			**0.43**
Predicted Condition State (thresholds : 0, 1.664)			**Bad (2)**

Based on these information, a more informative and cost-effective maintenance policy may be as follows:

Keep the truck in operation if performance value ≤ 0 *;*

Put the truck in the rear of the queue waiting for repair if $0 \leq$ *performance value* ≤ 1.664 *;*

Put the truck in the front of the queue waiting for repair if performance value ≥ 1.664 .

8.2.2. Prediction Ability

To assess the ability of prediction, the model was estimated using the first 150 observations and the results were used to predict the internal condition of the remaining 24 observations. The results of the estimation based on the first 150 observations are shown in Table 8.5. The performance thresholds were estimated as 0 and 1.657. The prediction for the remaining 24 observations is shown in Table 8.6. The true internal states are presented in the first column of the Table 8.6. and the predicted internal states in the second column. The detailed prediction for each truck is presented in the last three columns. For example, for truck 1, it was predicted to be in "bad" state while it was actually in "normal" state. And, for truck 7, it was predicted to be in "normal" while it was actually in "bad" state. Similar to discrete choice case, it was calculated that the percentage correctly predicted for the trucks truly in "normal", "bad" and "poor" states are 16.67%, 92.31% and 0%, respectively.

More discussion is needed about the percent correctly predicted for observations in different states. Recall that, in discrete choice models, the percent correctly predicted for the trucks truly in "normal", "bad" and "poor" states are 33.33%, 69.23% and 0%, respectively. Therefore, it seems that, for either the discrete choice or the performance threshold models, the correctly predicted percent was high for the "bad" state trucks, low for "normal" and terrible for "poor" state trucks. One reason for the strong prediction for the "bad" state trucks relative to "normal" and "poor" state trucks is that "bad" state observations dominate the sample (97 out of 174, or 55.75% of the sample are observations in "bad" state). By nature of statistical inference, the accuracy of the prediction will be better for the obseration group dominating the sample. One reason for the poor prediction for "poor" state trucks may be the essential definition of the state. Since there was almost no observation which was in really bad internal condition, e.g. needing replacing whole bolster, the "bad" and "poor" states might not be very distinct.

Therefore, given the definition of the both internal and external varibales, the relative accuracy of the prediction for different groups of observations depends on the shares of each group in the entire sample. Hence the issue of sample design comes into the picture.

Table 8.5. The Estimation Based on the First 150 Observations

Independent Variable	Estimated Coefficient	t-statistics
constant	0.611	1.190
data90	-0.228	-0.832
pwp_R_fn	0.346	1.491
pwp_R_pr	-0.025	-0.084
pow_R	-0.070	-0.760
rpl_R_fn	0.080	0.313
rpl_R_pr	0.119	0.485
pwp_L_fn	0.273	1.052
pwp_L_pr	0.415	1.072
pow_ L	0.137	1.361
rpl_ L _fn	-0.674	-2.240
rpl_ L _pr	-0.256	-0.852
threshold 2	1.657	11.137
Summary Statistics		
log likelihood at convergence	-140.33	
log likelihood initial	-170.82	
number of observations	150	
goodness of fit	0.178	
percent correctly predicted	56.667	

Table 8.6. The Prediction for the Remaining 24 Observations Using the Estimation Based on the First 150 Observations

Observation	**True State**	**Predicted State**	**Normal**	**Bad**	**Poor**
1	1	2	w (N->B)		
2	2	2		r	
3	2	2		r	
4	2	2		r	
5	1	2	w (N->B)		
6	2	2		r	
7	2	1		w (B->N)	
8	2	2		r	
9	2	2		r	
10	2	2		r	
11	2	2		r	
12	2	2		r	
13	2	2		r	
14	1	2	w (N->B)		
15	1	2	w (N->B)		
16	1	1	r		
17	1	2	w		
18	3	2		r	w (P->B)
19	3	2			w (P->B)
20	3	2			w (P->B)
21	3	2			w (P->B)
22	2	2		r	
23	3	2			w (P->B)
24	2	2		r	
Percent Correctly Predicted			16.67%	92.31%	0%

Note: 1). w (F->B): wrong prediction to be "bad" while it is actually "normal".

2). w (B->F): wrong prediction to be "fine" while it is actually "bad".

3). w (P->B): wrong prediction to be "bad" while it is actually "poor".

4). r: right prediction.

In some practice, the structure of the sample may not be designed to be consistent with the true structure of the population. Rather, it is designed artificially to oversample certain observation group(s) against the other(s) for certain practical purpose, e.g. saving cost. Specifically, the share of certain group of observations may be biasedly oversampled in order to obtain higher accuracy of prediction because the prediction mistakes for this group are more costly than for the others. In the truck inspection case, if the miss-failure cost is more than the false-alarm cost and hence more accurate prediction for "poor" state is needed, the sample should really contain a larger share of "poor" state observations than the true population contains. Unfortunately, this was not the case in the data set available for this research.

Nonetheless, valuable information are still provided by the current results. Notice that most of the wrong prediction for "poor" state trucks were predicting true "poor" state truck as "bad". The reason for this may also come from the definition of the "bad" and "poor" states. This result may be acceptable in that, as mentioned previously, more concerns in practice are put on deciding whether the truck internal condition is in "normal" state or not. Therefore, it may not be inappropriate to combine the "bad" and "poor" states to be a single "abnormal" state. It can then be calculated that 83.33% and 93.75% correctly predicted for the "abnormal" state for discrete choice and performance threshold cases, respectively. This can be illustrated in the Table 8.7.

Table 8.7. Correct Prediction for Different Inspection Strategies for the remaining 24 Observations

	Discrete Choice Model	Performance Threshold Model	All "Normal"	All "Abnormal"
Normal	33.33%	16.67%	100%	0
Abnormal	83.33%	93.75%	0	100%

As shown in the last two columns of the table, if we take the strategy of either taking all the truck's internal condition as "normal" or all "abnormal", we would end up with one of two results: either predicting the "normal" internal state truck 100% correctly but failing entirely for the "abnormal" state trucks, or the reverse case. But if the strategy introduced by the discrete choice model is taken, we would have 33.33% correct prediction for the "normal" state trucks, and 83.33% for the "abnormal" state trucks. Similarly, if the strategy introduced by performance threshold model is taken, we would have 16.67% correct prediction for the "normal" state trucks, and 93.75% for the "all abnormal" state trucks. Whether the strategies introduced by the two models are better than "all normal" and/or "all abnormal" strategies depends on the cost structure. More specifically, it depends on the share of "poor" state truck in the population and the relative magnitude of miss-failure vs. false-alarm cost. If the "poor" state trucks account for a very large portion of the entire truck population and the miss-failure cost is much higher than false-alarm cost, then "all abnormal" may be more appropriate strategy to take than the strategies resulting from the current models. But the best strategy will probably be provided by models using a better designed sample biasing towards the "abnormal" state trucks, and better collected data and better designed survey containing more comprehensive and accurate data. By biasedly oversampling the "abnormal" state observations, the prediction quality for the state will increase. By better survey design and data collection, the prediction accuracy for both "normal" and "abnormal" states will increase.

8.3. Evaluation for the Performance Threshold Method

Compared to discrete choice method, performance threshold method is of slightly better quality in terms of goodness of fit. Performance threshold model has goodness of fit 0.185, and discrete choice model 0.176. In terms of the prediction quality, since in many cases miss-failure cost is believed to be more than false-alarm cost, performance threshold model may be better than discrete choice model. in the sense that it is more accurate to predict the "abnormal" state trucks.

The most appealing aspect of the performance threshold against discrete choice method is its stronger underlying behavioral theory, i.e. performance function theory. As presented previously, it is essentially not appropriate to consider the truck internal condition as discrete alternatives, like transportation modes (train or intermodal). Rather, the internal condition, which is the dependent variable in the models, should be considered as continuous, or at least, a series of discrete states with certain order (e.g. from "perfect", "good", "OK" ... to "really bad"). The most important assumption on which the performance function theory is based is the ordinal discrete nature of dependent variable. Obviously, the method makes more behavioral sense to address the issue.

Chapter 9

Summary, Conclusion and Future Direction

9.1. Summary of the thesis

In essence, the problem this thesis copes with is the false-alarm and missing-failure costs in the repair and inspection of freight railroad car truck internal area. This comes from the difficulty to inspect the true internal truck condition due to the physical nature of the car and truck. Trying to solve the problem, or reduce the costs, this thesis seeks to predict the freight railroad car truck internal condition from the external condition. To do this, two main statistical methods were raised by the thesis, i.e. discrete choice method and performance threshold method. Precisely speaking, this thesis should belong to the domain of condition-based predictive inspection and maintenance technique.

Some basic knowledge in three major disciplines are involved in the research, i.e. machinery inspection and maintenance; freight railroad car truck mechanics, inspection and maintenance; and the theoretical basis for the statistical methods employed. The related basic knowledge in these three disciplines are addressed in Chapter 2, 3, and 4, respectively.

A case study was conducted. The two proposed methods and a linear regression model were applied using a data set provided by a Canadian company, Sultran LTD. The case study is presented in chapters 5, 6, 7 and 8. Based on theoretical basis and the results from the case study, some conclusions can be drawn.

9.2. Conclusion

In general, the methods which have been mentioned and discussed in this thesis can be divided into two groups. One group is the linear regression models discussed in chapter 6. The other is the set of models including the discrete choice models and the performance threshold model which are discussed in chapter 7 and 8, respectively, and the discriminant analysis method which is reviewed in chapter 2.

The later models are better than linear models in that they provide better estimation and information on which more cost-effective maintenance decisions can be made. By nature of the data collection, the internal truck condition as dependent variable is not continuous but discrete levels of condition. This limits the applicability of the linear regression models because linear regression is based on the assumption that the dependent variables are continuous. The subsequent models are based on the discrete nature of the dependent variable and seek to link the internal condition with external condition by either linking the probabilities of internal truck condition being in different states with the external measurement variables (discrete choice and discriminant models), or finding some way to assign the internal truck condition to a certain state (performance threshold model). The models provide not only better estimation but also more insight to the problem and hence more robust prediction.

Among the models, i.e. discriminant model, discrete choice model and performance threshold model, the following comparative conclusion can be made from the perspectives of underlying behavioral theory and computation.

In terms of underlying behavioral theory, the performance threshold method is the strongest one. Two important behavioral assumptions are made in performance threshold method. The first is that there is an underlying performance of internal truck area which can be indicated by external condition and hence expressed as a linear function of external measurement variables. The second is that the dependent variable, internal condition, is an ordinal discrete variable, which can be identified by certain thresholds. The method seeks essentially to find the underlying performance function and thresholds of performance. These two assumptions make sense because they are consistent with the true situation in practice. Therefore, this method is very appealing. Relative to performance threshold method, the weakness of the discrete choice is the assumption that the dependent variable, internal condition, is a variable of several independent discrete states. As presented previously, this is not consistent with the true situation.

In terms of the computation, some observations can be made as follows. The discrete choice and performance threshold methods can be implemented using existing statistical software. SST (Statistical Software Tools) was used in the research of this thesis. To implement discriminant model, certain programs would probably have to be written by the users.

From the results of models, it can also be observed that performance threshold model provided relatively better estimation and prediction than discrete choice model did. The reasons for this can be addressed, at least partially, by the above comparative analysis. Therefore, given the similar situation to the case study in this thesis, meaning similar objective, sample and survey designs, data collection, computer software available, and so forth, performance threshold method would be suggested as the first choice among the different methods involved in the thesis.

9.3. Future Direction

More work following this thesis should be done along two major directions, data and modeling. From data side, more work needs to be done to provide better data. First, it is obvious that a larger sample is always desired for better modeling analysis. Second, maintenance consideration should be reflected in the sample design. For example, if the maintenance emphasis is more on avoiding missing-failure cost, or put in other way, missing-failure cost is more significant than false-alarm cost, then more accurate estimation and prediction for the trucks in unacceptable condition is desired than for the trucks in acceptable condition. Therefore, unacceptable state trucks should be biasedly oversampled against acceptable state trucks. Third, more a comprehensive or proper survey should be designed to include additional potentially significant variables. For example, wedge rise should be included into the inspection of external measurement variables. Fourth, more precise data collection should be pursued. Specifically, certain qualitative variable, if possible, may be considered to be quantified. If not, more precise judgment may be pursued in order to reduce the subjectiveness, such as defining better judgment criterion and/or giving inspectors better training.

From the modeling side, further research should be done related to the correlation between the internal condition of two trucks of the same car. The first question is whether there is such a correlation. The reason for asking this question is quite intuitive. Since the freight railroad car is the most integrated unit in the whole train-track system, two trucks in the same car may be correlated each other. If there is correlation, then the next question must be what relation it is. Two hypotheses may be raised. One is positive correlation. This implies that if one truck is in unacceptable condition, the other one is probably also. The rationale behind this is that two trucks' condition are consistent with the whole car's system. The other hypothesis is negative correlation. This implies that if one truck is in unacceptable condition, the other is probably not in unacceptable condition. The rationale for this is that the truck which becomes worn first would act as the "wear plate" for the other truck and hence take most of the wear from the whole car. To answer these questions, more advanced methodological and computational tools are needed. Methodologically, this question will essentially introduce the issue of correlation between dependent variable (internal truck condition) of each pair of observations (two trucks of the same car). This will also introduce higher computational complexity.

Practically, some work involving both data and modeling may be more achievable than the aforementioned work. In practice, inspection and/or repair managers often face certain limits. Therefore, the managers' objective is usually reducing the cost as much as possible without exceeding the limits, rather than knowing the true truck condition and making maintenance decision basd on the condition. The two typical limits are constraints on the repair facility and the limit of poor truck performance. For the former case, if the repair facility is congested, then the objective becomes avoiding "false-alarm" and more accurate prediction for the trucks in acceptable internal state is desired. For the latter case, if some poor truck performance is experienced (e.g. derailments caused by problematic truck operation), then the objective becomes avoiding missing-failure and more prediction for the trucks in a highly unacceptable internal state is desired. Therefore, for either case, a binary model is probably more desirable in practice. The model may provide a threshold of probability (if discrete choice model) or a threshold of performance (if performance threshold model), by which the managers can decide whether to take the car into repair shop or not. In order to have accurate prediction for either case, objective-specified sample design must be conducted as mentioned above. If the objective is to avoid false-alarm, then acceptable state truck should be oversampled. If the objective is to avoid really bad trucks, then really bad trucks should be oversampled.

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APPENDIX:

Program for the Modeling Using SST (Statistical Software Tools)

```
spool file [appendix.out] out

read to [serial car_no car_end pwp_R pow_R rpl_R pwp_L pow_L rpl_L\
        int_exp int_cate] file [thesis.csv]
save file [thesis.sav]
load file [thesis.sav]


REM************************************************************************
REM                    VARIABLES PREPARATION
REM************************************************************************

set constant=1
set one=1
set zero=0

rem ====== 2 dummies for pwp_R ======
set pwp_R_fn=0
set pwp_R_fn=1; if[pwp_R==1 | pwp_R==2]

set pwp_R_pb=0
set pwp_R_pb=1; if[pwp_R==3]

rem ====== 2 dummies for rpl_R ======
set rpl_R_fn=0
set rpl_R_fn=1; if [rpl_R==1]

set rpl_R_pb=0
set rpl_R_pb=1; if [rpl_R==2]

rem ====== 2 dummies for pwp_L ======
set pwp_L_fn=0
set pwp_L_fn=1; if[pwp_L==1 | pwp_L==2]

set pwp_L_pb=0
set pwp_L_pb=1; if[pwp_L==3]

rem ====== 2 dummies for rpl_L ======
set rpl_L_fn=0
set rpl_L_fn=1; if [rpl_L==1]

set rpl_L_pb=0
set rpl_L_pb=1; if [rpl_L==2]

rem ====== 3 choices ======
```

```
set intcate1=0
set intcate1=1; if [int_cate==1]
set intcate1=2; if [int_cate==2 | int_cate==3]
set intcate1=3; if [int_cate==4]

rem ====== dummy for 90 / 92 data ======
set data90=0
set data90=1; if [serial>54]



REM*************************************************************************
REM                                    MODELING
REM*************************************************************************

rem======================================
rem    ORDINAL PROBIT
rem======================================

rem==== Final Model ====
prob dep[intcate1] ind[constant data90 \
                        pwp_R_fn pwp_R_pb pow_R rpl_R_fn rpl_R_pb\
                        pwp_L_fn pwp_L_pb pow_L rpl_L_fn rpl_L_pb]\
          if[intcate1!=0]

rem======================================
rem    MULTINOMIAL LOGIT
rem======================================

rem==== Model Specification C ====
mnl dep[intcate1] ivalt[ constant_1:one zero zero \
                         constant_1:zero one zero \
                         \
                         data90_2:zero data90 zero \
                         \
                         pwpRfn_1:pwp_R_fn zero zero \
                         pwpRfn_2:zero pwp_R_fn zero \
                         \
                         pwpRpb_1:pwp_R_pb zero zero \
                         pwpRpb_2:zero pwp_R_pb zero \
                         \
                         powR_1:pow_R zero zero \
                         powR_2:zero pow_R zero \
                         \
                         rplRfn_1:rpl_R_fn zero zero \
                         rplRfn_2:zero rpl_R_fn zero \
                         \
                         rplRpb_1:rpl_R_pb zero zero \
                         rplRpb_2:zero rpl_R_pb zero \
                         \
                         pwpLfn_1:pwp_L_fn zero zero \
```

```
                pwpLfn_2:zero pwp_L_fn zero \
                \
                pwpLpb_1:pwp_L_pb zero zero \
                pwpLpb_2:zero pwp_L_pb zero \
                \
                powL_1:pow_L zero zero \
                powL_2:zero pow_L zero \
                \
                rplLfn_1:rpl_L_fn zero zero \
                rplLfn_2:zero rpl_L_fn zero \
                \
                rplLpb_1:rpl_L_pb zero zero \
                rplLpb_2:zero rpl_L_pb zero ]\
        if[intcate1!=0]


REM**********************************************************************
REM                       PREDICTION
REM           (using the first 150 obs for estimation, predict
REM           on the remaining 24 obs of the same sample structure)
REM**********************************************************************

rem========================================
rem   ORDINAL PROBIT
rem========================================

rem==== the first 150 obs ====
prob dep[intcate1] ind[ constant data90 \
                pwp_R_fn pwp_R_pb pow_R rpl_R_fn rpl_R_pb\
                pwp_L_fn pwp_L_pb pow_L rpl_L_fn rpl_L_pb]\
        if[intcate1!=0 & serial<199] coef[a]

rem==== predict on the remaining 24 obs ====
set perf=a[1]+a[2]*data90+ \
        a[3]*pwp_R_fn+a[4]*pwp_R_pb+a[5]*pow_R+\
        a[6]*rpl_R_fn+a[7]*rpl_R_pb+\
        a[8]*pwp_L_fn+a[9]*pwp_L_pb+a[10]*pow_L+\
        a[11]*rpl_L_fn+a[12]*rpl_L_pb

print var[intcate1 perf] if [serial>=199]

rem========================================
rem   MULTINOMIAL LOGIT
rem========================================

mnl dep[intcate1] ivalt[ constant_1:one zero zero \
                constant_2:zero one zero \
                \
                data90_2:zero data90 zero \
                \
                pwpRfn_1:pwp_R_fn zero zero \
                pwpRfn_2:zero pwp_R_fn zero \
```

```
                    \
                    pwpRpb_1:pwp_R_pb zero zero \
                    pwpRpb_2:zero pwp_R_pb zero \
                    \
                    powR_1:pow_R zero zero \
                    powR_2:zero pow_R zero \
                    \
                    rplRfn_2:zero rpl_R_fn zero \
                    \
                    rplRpb_1:rpl_R_pb zero zero \
                    rplRpb_2:zero rpl_R_pb zero \
                    \
                    pwpLfn_1:pwp_L_fn zero zero \
                    pwpLfn_2:zero pwp_L_fn zero \
                    \
                    pwpLpb_1:pwp_L_pb zero zero \
                    pwpLpb_2:zero pwp_L_pb zero \
                    \
                    powL_1:pow_L zero zero \
                    powL_2:zero pow_L zero \
                    \
                    rplLfn_1:rpl_L_fn zero zero \
                    rplLfn_2:zero rpl_L_fn zero \
                    \
                    rplLpb_1:rpl_L_pb zero zero ]\
          if[intcate1!=0 & serial<199] coef[b]

set u1= b[1]+b[4]*pwp_R_fn+b[6]*pwp_R_pb+b[8]*pow_R+b[11]*rpl_R_pb+\
        b[13]*pwp_L_fn+b[15]*pwp_L_pb+b[17]*pow_L+b[19]*rpl_L_fn+\
        b[21]*rpl_L_pb
set u2= b[2]+b[3]*data90+b[5]*pwp_R_fn+b[7]*pwp_R_pb+b[9]*pow_R+\
        b[10]*rpl_R_fn+b[12]*rpl_R_pb+b[14]*pwp_L_fn+b[16]*pwp_L_pb+\
        b[18]*pow_L+b[20]*rpl_L_fn
set u3=0

print var[intcate1 u1 u2 u3] if[serial>=199]


spool off
```