
A Failure Rate Analysis of Complex Vehicles

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Abstract: When engineered items fail, there are often indicators of decay long before the system collapses. This research explores this concept applied to complex vehicles operated in public transportation, and the results can be extrapolated to any vehicle system. Transit bus reliability data gathered from eight transit agencies distributed across the United States are analyzed at a vehicle and subsystem level to identify system failures. An analysis of vehicle subsystem component failures is conducted, where the theory of reliability of repairable systems is applied to the in-transit data to determine if major component failures can be detected by increases in cumulative and subsystem failure rates. Thus, the impact of the research illustrates that major repairs might be detected far in advance of when they are needed.

Keywords: Complex Vehicle Reliability, Failure Rate, Bathtub Curve, Repairable Systems, Bus Testing

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1 Introduction

The majority of Americans using public transportation choose transit bus service as their primary carrier (USDOT-BTS 2002). And, according to a 2002 Bureau of Transportation Statistics (BTS) study, 60% of all public transportation is represented by transit bus ridership (USDOT-BTS 2002). Nationwide, there were more than 500 million individual transit bus trips made in January 2002 alone. According to a 2005 survey, BTS statistics show that 4.4% of working Americans use public transportation to get to work(USDOT-BTS 2005). This percentage has remained constant since 1989, even though the amount of working Americans has increased by 14% (USDOT-BTS 2005). Thus, the total usage of public transit is steadily growing.

Transit buses are consistently the most widely used form of public transportation due to schedule flexibility, route flexibility, and affordability. Even though transit bus ridership represents 60% of all public transportation utilization, the American Public Transportation Association (APTA) reported that only 46.5% of public transportation revenues were generated from transit bus ridership (APTA 2004). The affordability of transit bus service makes it extremely appealing with ever-increasing fuel and automobile maintenance costs. Automobile owners are paying premium costs to operate their vehicles on a daily basis in both operating costs and total annual costs, estimated between 12.1 and 17.0 cents/mile in 2000, depending on the type of automobile considered (Runzheimer 2005). Transit bus service costs, on the other hand, totaled only 20 cents/mile in 2000, implying consistently low ticket costs when spread over the typical in-service occupancy (Runzheimer 2005).

In order to keep public transportation costs low and services reliable, vehicle maintenance must be timely and efficient. In 1987, Congress passed the Surface Transportation and Uniform Relocation Assistance Act (STURA) (Pub. L. No. 100-17) which was an amendment to Section 12 of the Federal Transit Administration (FTA) Act of 1964 (US-GAO 1987). STURA established that after September 30, 1989, no new bus models may be purchased with federal funds unless it was first tested at an approved bus testing facility. In response, the Altoona Bus Research Testing Center (ABRTC), in conjunction with The Pennsylvania State University and the Federal Transit Administration, was established in 1988 to meet the new bus testing needs.

The objective of durability tests performed at the Pennsylvania Transportation Institute (PTI) are to accelerate the damage inflicted on a bus through a shorter mileage than would be experienced during in-transit usage. The bus is tested on a durability track which consists of seven distinct pavement discontinuities that simulate in-transit conditions. The testing performed at PTI allows transit operators to select a well-performing model in order to reduce their operating costs and eliminate any fleet downtime. In addition to the bus testing program at Penn State, other researchers have investigated methods of increasing vehicle and component reliability by exploring a variety of concepts.

Previous researchers at Penn State have investigated results produced by the bus testing program. Heverly (Heverly 1991) researched a accelerated-based correlation method to relate transit bus service life events with similar events experienced at the Pennsylvania Transportation Institute (PTI) durability test track. Heverly studied forces (accelerations) seen by the bus frame relating to various pavement discontinuities.

nuities. Then a correlation equation was used to determine the number of times each proving ground element should be traversed during testing to represent the entire service life. Fisher (Fisher 1992) expanded on Heverly's work (Heverly 1991) by using test track and transit service data to analytically determine "compressibility factors" for various vehicle components encountered by traversing various pavement discontinuities. His work focused on determining a compressibility factor for air springs by measuring the vertical displacement of the suspension system and body due to pavement discontinuities.

Klinikowski *et al.* (Gilmore, Klinikowski & Kulakowski 1999) conducted a study on the correlation of data obtained at the transit bus testing program at the Pennsylvania Transportation Institute (PTI) with in-transit bus failures. In-transit failure data was collected for from two different transit agencies for three different bus models, with ten buses worth of data for each model. The in-transit data was broken into subsystem occurrences, and then was compared to data from PTI tests on the basis of number of failures. The two data sets were then compared with a rank correlation coefficient to determine how well the transit data compared to test track data. The data correlated with $r=0.944$ with a 99% confidence interval, which indicated that there was a very good correlation between in-service and test track failures.

Other researchers have contributed towards vehicle reliability by investigating the effects of failures on the performance of system. Binggang and Shuijun (Binggang & Shuijun 1985) developed methods to evaluate the reliability of automotive products by categorizing failures according to degree of harmfulness and determining weighting coefficients for each failure and, subsequently, an equivalent number. Singh and Kankam (Kankam & Singh 1979) reported their effort of creating a database for reliability of transit vehicles and their components. Their research involved collecting failure data on 500 subway cars, 400 streetcars, and 1,100 buses from the Toronto Transit commission.

Horvath and Wasiloff (Horvath & Wasiloff 1994) of Ford Motor Company studied the process for extrapolating test data from the manufacturing process to predict high mileage reliability of vehicles. Their study focused on ways to determine long term product reliability in the manufacturing or design stage of product of development, rather than relying on customers identifying critical design flaws via warranty claims or complaints. Capitano, Anderson, and Sverzhinsky (Capitano, Anderson & Sverzhinsky 2000) wrote about accelerated aging experiences of Siemens NAMO, a manufacturer of electric motors/drives. Siemens NAMO implemented an accelerated-aging test program (simulation) to reduce durability test time without drastically increasing overhead by purchasing expensive testing equipment. Based on these results, Siemens reduced their test times significantly; for example, a system whose designed life is 2,000 hours was able to be tested in less than 170 hours with accelerated aging simulations.

Fenton (et. al.) (Fenton, Neil & Marquez July 1-4, 2007) examined reliability through continuous node Bayesian Networks to predict software defects and software reliability. Their approach incorporated obvious and simple causal factors that can lead to a better understanding of what was observed during reliability prediction and testing. Strutt (et. al.) (Strutt, Loa & Allsopp 1998) introduced his research on predicting human reliability during a predetermined task sequence. Their research is based on probabilistic models that enable error-promoting condi-

tions in accident scenarios to be modeled explicitly, along with a time-dependent probability of error estimation. Their research presents an example of the reliability of a driver in a wreck scenario, which is an unintended but very real cause of unexpected transit bus reliability.

2 In-Service Data

The goal of this research is to outline a methodology for investigating vehicle reliability by inspecting the failure rate. Ultimately, we want to predict vehicle failures before they occur to protect passengers, reduce operating costs, and in the case of transit vehicles, to maintain route schedules. To achieve this goal, data was sought from various transit agencies around the continental United States.

In an effort to obtain reliability data, fourteen transit agencies were contacted between April and December 2007 (Figure 1). Agencies were chosen to represent a large geographical distribution across the United States. The data requested from each agency required two key components:

- A description of any non-scheduled maintenance performed on the bus
- An associated mileage

When the data collection stage of the project ended in December 2007, a total of eight agencies supplied data (Figure 2). After collecting the data, the reliability instances were classified based on their severity and impact on the transit schedule and passenger safety. This classification was based on failure definitions suggested by the National Transit Database, which included major and minor failures, discussed below.

3 Data Classification

The distinction between major and minor failures must be clear in order for any analysis presented herein to have relevance. One classification methodology is suggested by the National Transit Database (NTD). The NTD is the Federal Transit Administration's (FTA) primary database for transit industry statistics including financials, fleet composition, ridership, and other pertinent information (FTA 2004). Any agency receiving federal funds to purchase fleet vehicles is required to submit these operational statistics yearly to the NTD. These agencies are required define the failures that their fleet vehicles experienced during each operating year. The NTD categorizes failures based on the following criteria (FTA 2004):

- **Major Failure:** A failure of some mechanical element of the revenue vehicle that prevents the vehicle from completing a scheduled revenue trip or from starting the next scheduled revenue trip because actual movement is limited or because of safety concerns.
- **Minor Failure:** A failure of some mechanical element of the revenue vehicle that, because of local agency policy, prevents the revenue vehicle from completing a scheduled revenue trip or from starting the next scheduled revenue trip even though the vehicle is physically able to continue in revenue service.

While these guidelines define an outline for data classification, a more stringent approach was taken when categorizing data for this work because repair descriptions often do not make clear whether a failure disabled the vehicle. For this study, **any** repair corresponding to a **critical system** of the bus was classified as a major failure. This keeps the classification process focused on the easier task of determining which system exhibited a failure rather than how it failed and to what degree.

For instance, consider brake failures: According to the NTD's definitions, slack brakes or brake replacements might not be considered a major failure because these items could be replaced at the bus's next scheduled preventative maintenance (PM). However, for the purposes of this study, any failure relating to the brakes was classified as a major failure, as well as any other component directly on the drivetrain. Examples of other systems that automatically received a "major failure" classification include:

- Transmission and components
- Suspension and components
- Vehicle frame
- Steering and components
- Power plant and components
- Any safety equipment

Examples of failures that would be classified as major include:

- Turbo replacement
- Engine overheating or radiator issues
- No start/starter issues/glow plug replacements

Conversely, a minor failure was determined to be an issue that allows the bus to maintain its schedule, but requires repair at the next available opportunity. Minor failures may cause the passenger slight discomfort, but would not endanger the safety or wellbeing of a patron. It was recognized that some minor failures could endanger the passenger in extreme cases. For example, all heating and air conditioning failures were classified as minor failures. However, if a transit bus operating in Alaska loses heat on a rural route, the results could very well endanger patrons. Nonetheless, this would still be a minor failure in our reclassification despite the impacts. Examples of minor failures encountered in data classification include:

- Heating/Air Conditioning issues
- Lamps in need of replacement
- Torn seats/ damaged passenger compartment
- Windshield wipers
- Farebox repairs

By following these guidelines, readers can understand the methodology employed to categorize the data analyzed in this study.

4 Failure Rate Analysis

4.1 Failure Rate Theory

The failure rate of a system describes the frequency with which failures occur (Kececioglu 1991). If the progression of total failures, $F(t)$, is known, then the failure rate can be determined numerically by (Modarres. M & Krivtsov 1999):

$$h(t) = \lim_{\tau \rightarrow 0} \frac{1}{\tau} \left(\frac{F(t + \tau) - F(t)}{R(t)} \right) \quad (1)$$

where

$$\begin{aligned} t &= \text{time} \\ \tau &= \text{time increment} \\ R(t) &= \text{system reliability} \end{aligned}$$

Additionally, the probability that the item will fail before or up to time t , $F(t)$, is defined as (Modarres. M & Krivtsov 1999):

$$F(t) = Pr(T \leq t) \quad (2)$$

For non-repairable systems, if the failure rate, $h(t)$, is plotted versus time, it generally exhibits a bathtub shape, and thus is referred to as the *bathtub curve* (Figure 3)(NIST 2006). The bathtub curve can be broken into three distinct periods. The first period is known as the *Infant Mortality* or *Burn-In* period. This period represents the beginning of a product's life cycle, where the failure rate starts off very high, but also decreases rapidly (NIST 2006). The next period, characterized by a somewhat constant failure rate where mostly random failures occur, is known as the *Useful Life* (NIST 2006). A well-designed product spends most of its life here. The final period, characterized by an increasing failure rate, is called *Wear-Out* (NIST 2006). It is during this period that a component or system would be replaced because it has outlived its useful life. While a transit bus is a repairable system, the above definitions of reliability trends for non-repairable systems are useful to understand the discussion that follows.

4.2 Calculating the Failure Rate

In this study, the failure rate is defined as the number of failures per unit distance traveled during in-service operation (Equation 3). For the purposes of this study, the failure rate of any bus is defined as the derivative with respect to distance of the cumulative failures. Note that Equation 3 agrees with Equation 1 if reliability, $R(t)$ is 1, and distance is used instead of time.

$$\text{Failure Rate} = \lim_{\Delta \text{distance} \rightarrow 0} \frac{\Delta \text{failures}}{\Delta \text{distance}} \quad (3)$$

The cumulative failure data consists of a discrete set of data points, inhibiting the calculation of the exact derivative per Equation 3. Numerical differentiation

deals with this type of data; it is a process by which approximate derivatives are obtained from a set of discrete data points. The approximate derivative can be calculated by numerous methods, three of which are considered here:

- The discrete data can be plotted and fit either locally or globally with a polynomial curve. The approximate derivative can then be calculated by taking the derivative of the function that describes the curve fit.
- The discrete data can be differentiated by developing a *sliding window* approximation of the derivative by defining a window of fixed interval width, summing the number of failures in the fixed interval, and repeating this process as the window is slid throughout the entire range of the data.
- The derivative can be obtained by calculating numerically with the Euler approximate derivative by calculating the failures per mile throughout the duration of the data.

To describe and compare these in more detail, the sliding window method (Figure 4) uses intervals of fixed width of 10,000 miles. The total number of failures in the window, n , were summed. The window was then slid δ units (e.g. 100 miles) and another value of N was calculated and appropriately located at the midpoint of the window in its new location. The window was repeatedly slid δ units until an approximate derivative of all m miles of data had been calculated. Thus, the failure rate obtained from a sliding window approximation would be on the order of failures per 10,000 miles.

A second method of determining the failure rate involves fitting the cumulative number of failures versus miles with an n^{th} degree polynomial function, and taking its derivative with respect to mileage. A 6^{th} degree polynomial function is used in this research, and it was found that this degree polynomial does not capture sudden changes in slope that might provide additional insight of the failure rate. The sliding window, on the other hand, captures the local variations in the data because of the method of derivative calculation. The sliding window is also an advantageous choice for failure rate calculation because its method is easy to understand and explain to our end customer - the transit agency operator. When the two methods are compared for an arbitrary bus, the increased detail of the sliding window approach is clearly evident (Figure 5).

The final method of determining the failure rate involves calculating derivative using Euler's numerical approximation method. This method expresses the failure rate as failures per mile. The failure rate is calculated as the slope between each neighboring failure instance, rather than a window of 10,000 miles or a polynomial fit. The derivative is calculated as:

$$\text{Failure Rate}(i) = \frac{\Delta Y}{\Delta X} = \frac{\text{failures}(i+1) - \text{failures}(i)}{\text{miles}(i+1) - \text{miles}(i)} \quad (4)$$

To smooth the curves, the derivative is forward and backward filtered with a 2^{nd} order lowpass digital Butterworth filter, with cutoff frequency ω , where $0 < \omega < 1.0$, with 1.0 corresponding to half the sampling rate ((Mathworks 2007)). The cutoff frequency employed in this work was arbitrarily chosen as 0.3 after running the algorithm for various other values with minimal change. Further, the data is

analyzed again to remove outliers by eliminating any derivative value more than three standard deviations from the mean such that:

$$[\text{failure.rate}(i) - \text{mean}(\text{failure.rate})] > 3 \times \text{std.deviation}(\text{failure.rate}) \quad (5)$$

Graphically, the numerical and sliding window failure rates are plotted as Figure 6.

Note that the failure rate plots generated with the sliding window and euler exhibit the same behavior. Further, the two methods are basically the same, where the Euler derivative calculates a slope based on consecutive failure instances and the sliding window accomplishes the same result using a window of 10,000 miles. If we were to specify a sliding window size equal to the distance between consecutive failures, it would yield the Euler derivative. We chose the sliding window method in this research because of its simplicity and ease.

4.3 Buses Modeled as Repairable Systems

As previously stated, the bathtub curve graphically illustrates typical trends that occur during the life cycle of a product, including wear-in, useful life, and wear-out. But, pure bathtub curves apply to non-repairable systems. For repairable systems, we expect to see repeated bathtub curve effects corresponding with recurring break-in cycles of replaced or repaired components. A vehicle falls in the category of a repairable system where components that fail can be replaced to extend the overall useful life of the entire system.

For example, consider the failure rate plot of Bus P5002 (Figure 8). The failure rate in Figure 8 exhibits what seems to be multiple wear-in/wear-out cycles. The failure rate appears to increase and peak quite dramatically between 230,000 and 240,000 miles, and subsequently drop off. This trend repeats itself multiple times over the life of this bus. This type of behavior would be exhibited in a repairable system during its useful life. To verify this phenomena was not unique to this particular bus, the failure rate was plotted for numerous buses (Figure 7 - 9). The same results were observed in each bus investigated. The fact that such trends are seen in multiple buses from multiple agencies suggests that these are not anomalies in the data.

The trends in Figure 7 - 9 resemble repeated bathtub curves, with multiple wear-in/wear-out cycles. Multiple bathtub curves exhibited by a single system often reflect component replacements that contribute to the cumulative failure count of the system. In order to determine if the repeated peaks are repeated birth/death cycles, the mileage corresponding to these failure rate peaks was inspected throughout the in-transit data to locate any major component replacements.

4.4 Analysis of Failure Rate Peaks

The peaks observed in the failure rate are now examined to determine if they correspond with major component replacements or repairs. If repairs or replacements occurred near the peaks, then the peaks may be considered the start of a bathtub curve in the infant mortality period. Major component replacements are listed in Tables 1 - 3) and are shown in Figures 10, 11, and 12 along with corre-

sponding replacements discovered in the in-service data . It is quite clear that many of the peaks in the failure rate corresponded to major component replacements.

Table 1 Bus P5001 Component Replacements

Mileage	Description
228,594	Replace Generator
283,816	Replace Transmission
313,566	Replace Engine Assembly
339,122	Repair Transmission

Table 2 Bus P5003 Component Replacements

Mileage	Description
250,272	Replace Suspension
281,512	Replace Engine/Turbo
308,200	Replace Generator/Engine Component
347,398	Replace Water Pump
371,246	Replace Air System Controls

Table 3 Bus L9414 Component Replacements

Mileage	Description
261,718	Repair/Replace Generator
333,658	Replace R/F Leveling Valves
350,320	Multiple Engine Shutdowns (No Description of Action)
355,616	Transmission Slips/Slams (No Description of Action)
382,026	Overheating Engine Repairs (No Description of Action)

There were instances, however, where peaks existed that could not be attributed to any major repair. Thus, the next step was to compare the sliding window and Euler derivatives to verify the failure rates exhibited the same trends with separate methods. Plotting the filtered numerical derivative and sliding window derivative on the same plot gave insight into the validity of the peaks generated by the sliding window approach. The resulting plots are presented as Figure 13.

The trends exhibited by the filtered Euler numerical derivatives match well with the trends in sliding window derivatives. The peaks produced by the sliding window method also match with peaks in the Euler derivative. Thus, the peaks appear to be characteristics of the failure rate, and not of bad data processing.

4.5 Subsystem Failure Rate Analysis

The previous section suggests that many of the failure rate peaks have been found to occur near major component replacements or repairs. This section investigates whether major subsystems within a vehicle also exhibit failure rate, and whether these peaks also correspond to major repairs. For example, if a peak in the whole vehicle failure rate corresponds to an engine replacement, then a plot of the drivetrain failure rate is expected to peak near the engine replacement as well.

In order to look at the failure rate of individual subsystems, all of the in-transit data was recategorized into major subsystems including:

- Drivetrain: Any component associated with the engine, cooling system, and brakes.

- AC/Heat: Any component associated with air conditioning or heating
- Suspension: Any shocks, leaf or air springs, and/or air system repairs.
- Transmission: Any component associated with the transmission, drive shafts, differentials, and axles
- Steering: Any component associated with steering
- Frame and Mounting: Any repairs or replacements on the frame or structural mounting
- Wheels and Tires: Any flat tires, bent rims, or replacements
- Controls: Any electrical repairs that are responsible for control of some component
- Not Tested: Any component failure not tested for at PTI including windows, fareboxes, wheel chair lifts, and horns.

The sliding window derivative method is applied to the subgroups listed above to conduct a subsystem-level failure rate analysis. Only subsystem failure rates possibly related to major component failures are plotted. For example, if a particular bus has failure rate peaks that correspond to repairs in only drivetrain and steering, the failure rates of those subsystems only were plotted.

To illustrate this concept, consider Figures 14 and 15. This particular bus had multiple drivetrain and transmission failures. The other subsystems on the bus did not contribute significantly to the whole-bus failure rate. For example, the failure rates corresponding to air conditioning, frame, and wheels do not track with the whole-bus failure rate, which would be expected since no major repairs performed on this bus were associated with any of those systems.

Figure 16 illustrates the subsystem plots corresponding to the cumulative data shown in Figure 10. The failure rates of systems directly associated with peaks in the cumulative failure rate are plotted on the same graph. The generator replacement at mile 228,594 that corresponds with a peak in the cumulative failure also appears as a peak in the drivetrain subsystem. At transit agencies, generator failures are usually categorized with drivetrain failures because of their close association with the engine. The transmission replacement at 283,816 miles corresponds to a rise in both drivetrain and transmission failure rates. The engine replacement at 313,566 miles is also characterized by a rise in the drivetrain failure rate around this particular mileage. Finally, the transmission repair at 339,122 miles is characterized by an increase in both drivetrain and transmission subsystem failure rates.

Figure 17 showed the failure rates corresponding to Bus P5003. The solid arrow corresponds to major component repairs/replacements, and the dotted line corresponds to peaks in the subsystem failure rate. The suspension failure at 250,272 miles is not matched very strongly by the suspension failure rate. However the drivetrain rate does rise along with suspension, and peaks at about the same time as the suspension replacement. At 281,512, the engine/turbo replacement is matched exactly with a very distinct peak in drivetrain failure rate at the same mileage. The generator and engine component replacements at 308,200 is also characterized

by a rise in drivetrain failure rate. The increase and peak in drivetrain failure rate corresponds with the water pump replacement at 347,398 miles. Finally, there is a noticeable correlation between the air system controls replacement and the suspension failure rate.

Figure 18 shows the failure rates corresponding to Bus L9414. The increase in drivetrain failure rate corresponds with a generator replacement at 261,718 miles. There is also an increase in the suspension system failure rate near 333,658 miles, when the front and rear leveling valves were replaced. The drivetrain and transmission failure rates were elevated during the issues these subsystems experienced around 350,000 miles. Finally, after an overhaul at 382,026, the engine and cumulative failure rates decreased substantially.

Thus, our hypothesis of peaks in the subsystem failure rate matching with corresponding peaks in the cumulative failure rate appears to be confirmed qualitatively. This qualitative match is significant because it means that analysis of the failure rate on a subsystem level may enable a better understanding of the performance of the entire vehicle by suggesting the type of major failure that will likely soon occur. This agrees with intuition. For example, if one observes a rise in drivetrain subsystem failures, one can expect a greatly increased probability of a major drivetrain repair in the near future, and then decline in repairs thereafter.

A more formal analysis method is required to gain further insight into this phenomena, and to determine the statistical significance of the relationship between major component repairs and peaks in the failure rate.

5 Quantitative Analysis

In order to determine the statistical significance of the relationship between major component repairs and peaks in the failure rate, the inferred distances between the peaks and failure instances were analyzed. Consider Figure 19. First, we partition the data by defining the midpoint between peaks. If major repairs, R_i , occur independently of peaks, P_i , then Equation 6 should be uniformly distributed, where $d(i)$ denotes the distance between actual failure and peak, and $gap(i)$ denotes half the distance between peaks. Conversely, if there is a strong correlation, then Equation 6 should tend to be distributed near zero.

$$\frac{d(i)}{gap(i)} \quad i = (1, 2 \dots n) \quad (6)$$

To test the hypothesis, eight buses were chosen at random, and the ratio described in Equation 6 with respect to cumulative failures was plotted as a histogram to determine its distribution (Figure 20). The distribution yields a mean of 0.1748 when twenty seven failure instances were considered, which means the ratio tends to zero rather than being randomly distributed. To illustrate, the expected uniform distribution for Figure 20 is shown as a horizontal line at 3. Thus, there is a strong correlation between the existence of peaks in the whole vehicle failure rate, and corresponding major component repairs or replacements.

6 Conclusions

This research has shown that buses produce failure rate curves that exhibit repeated bathtub curve effects typical of repairable systems. The failure rate was calculated with several methods, and all show general agreement. Additionally, the data revealed that many of the peaks in failure rate correspond to major component replacements or system repairs. Numerous examples were presented which listed replacements and corresponding mileage. A subsystem level analysis was then conducted which noted that many peaks from subsystem failure rates correspond to peaks in the cumulative failure rate, and both peaks often correspond to major repairs. These results indicate that system failures may be identified and predicted on a subsystem level. Finally, peaks in the cumulative failure rate were verified to correspond with major component replacements or repairs by examining the distribution of the distance between failure rate peaks and reported failures.

The outcomes of this research are significant because they present a method of identifying vehicle failures from past data. The potential of conducting “real time” failure rate analysis using this method, coupled with advanced reliability modeling such as Weibull curve fits, could produce very accurate predictions of imminent vehicle component failure long before the the failure event takes place. Thus, major repairs may be planned for and possibly avoided before causing catastrophic damage to key vehicle components or before affecting the scheduled operation of a transit service vehicle.

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Figure 1 Summary of Contacted Agencies.



Figure 2 Summary of Agencies that Provided Data.

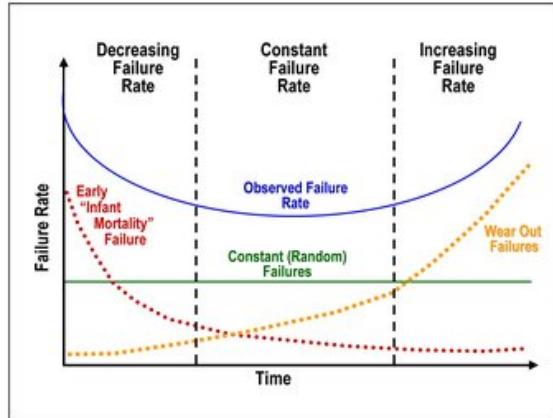


Figure 3 The bathtub curve.

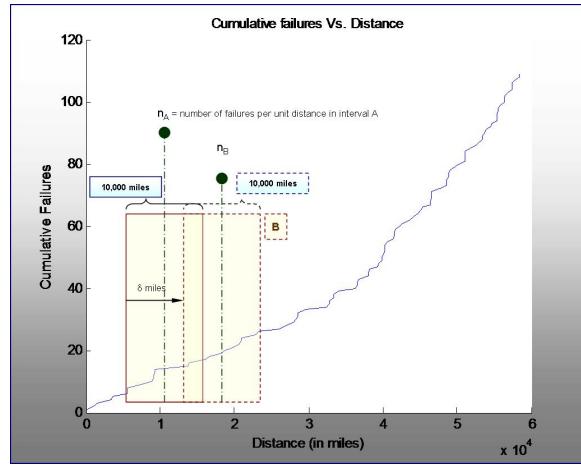


Figure 4 The Sliding Window Method.

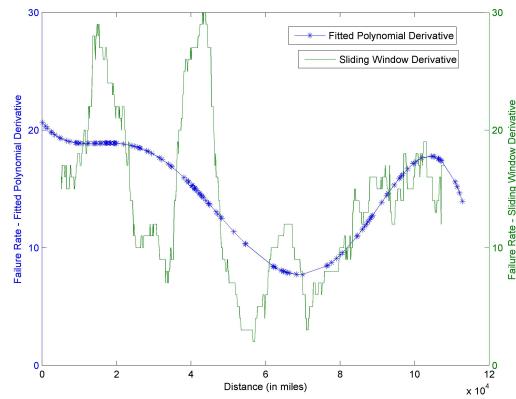


Figure 5 Comparison of the Polynomial Fit and Sliding Window Derivative Methods.

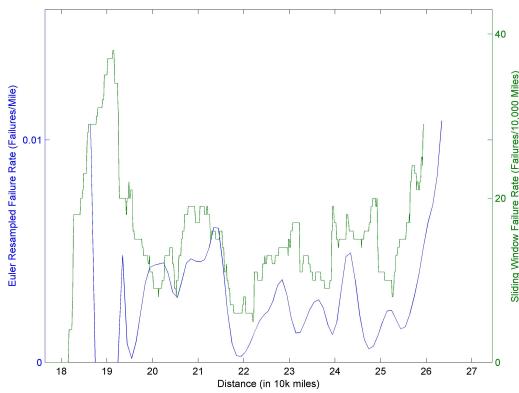
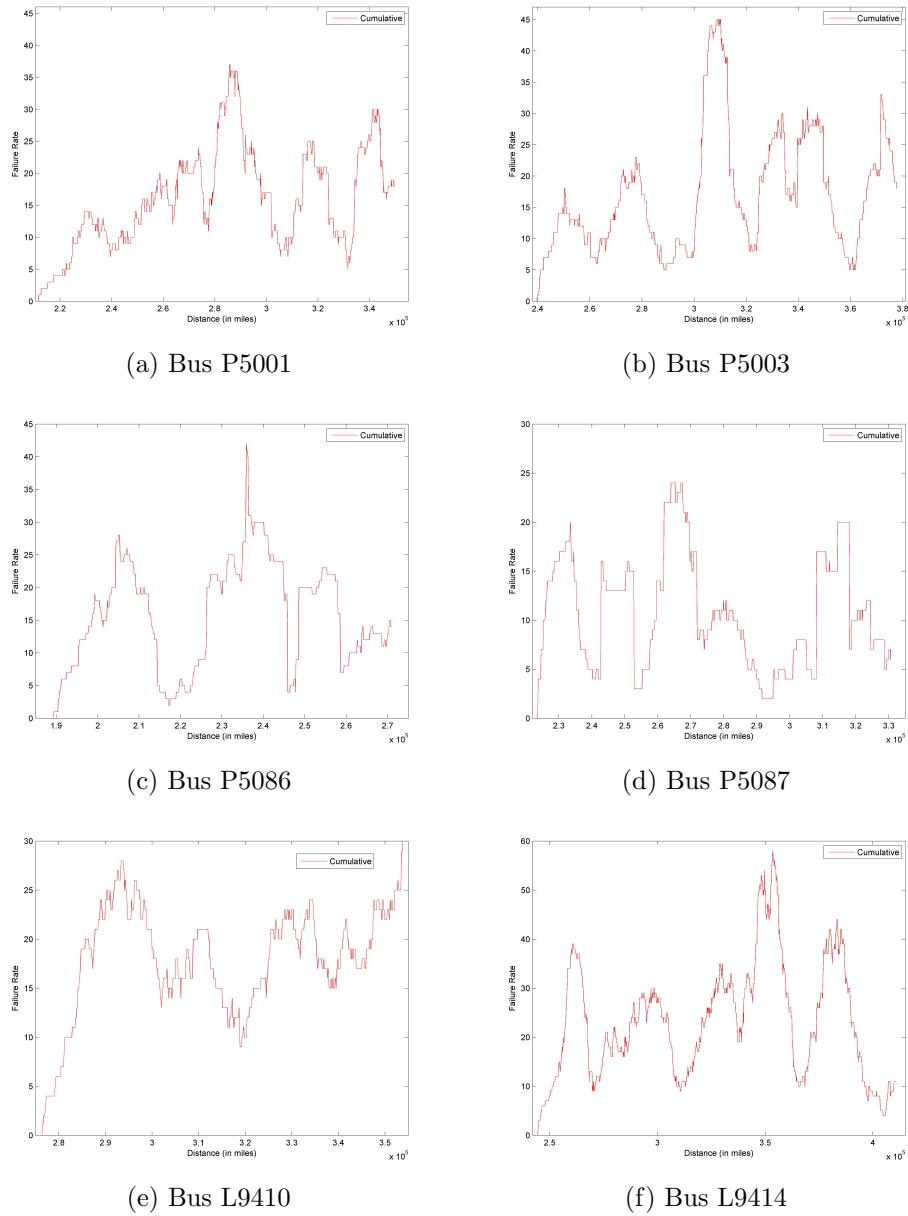


Figure 6 Filtered Numerical and Sliding Window Derivative Comparison.

**Figure 7** Selected Failure Rate Plots.

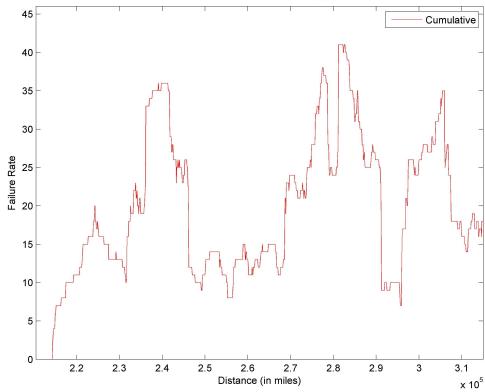


Figure 8 Bus P5002 - Failure Rate.

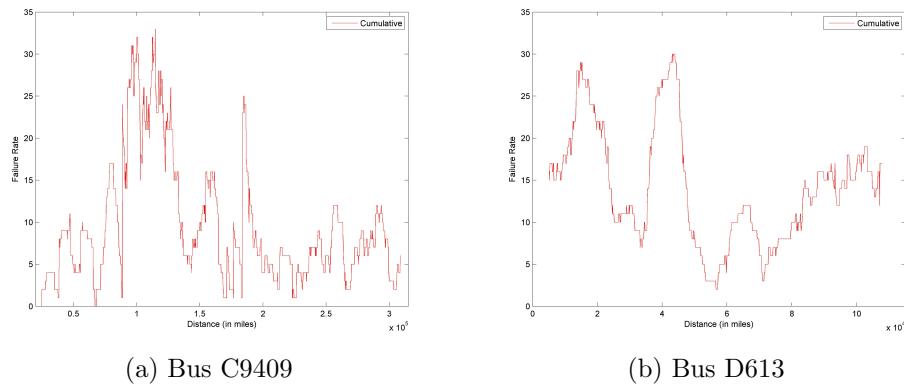


Figure 9 Additional Failure Rate Plots.

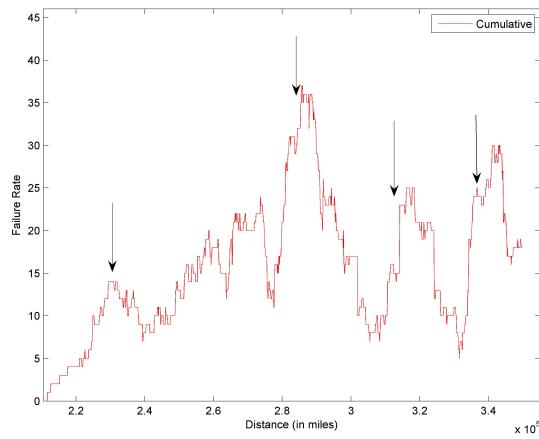


Figure 10 Bus P5001 - Component Replacements.

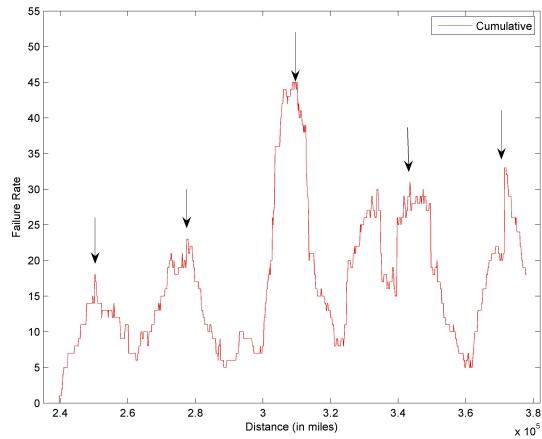


Figure 11 Bus P5003 - Component Replacements.

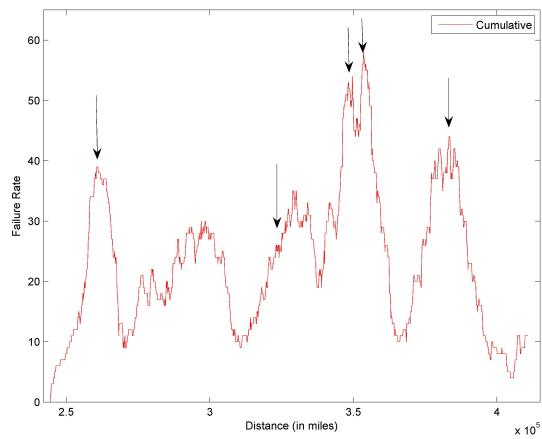


Figure 12 Bus L9414 - Component Replacements.

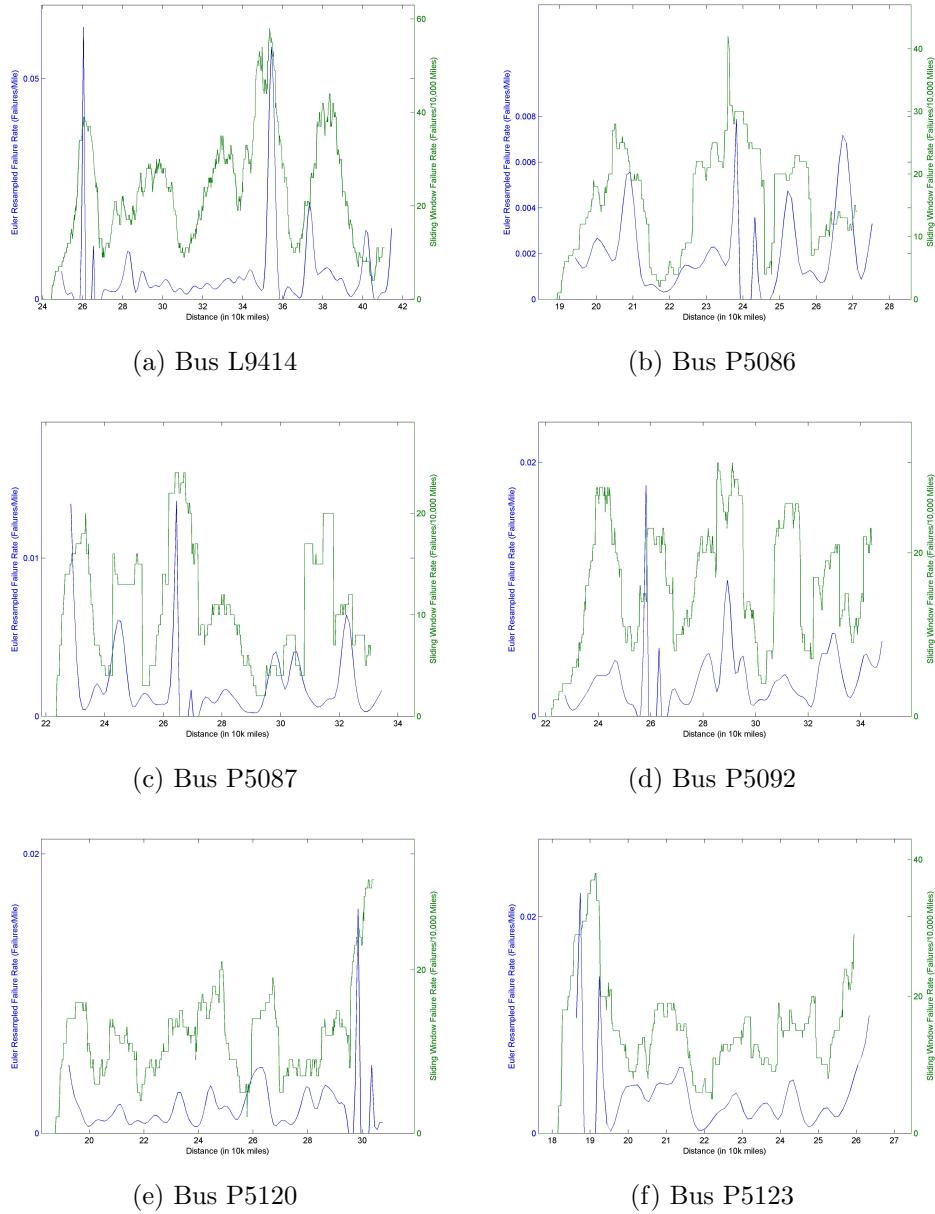


Figure 13 Filtered Numerical vs Sliding Window Derivatives.

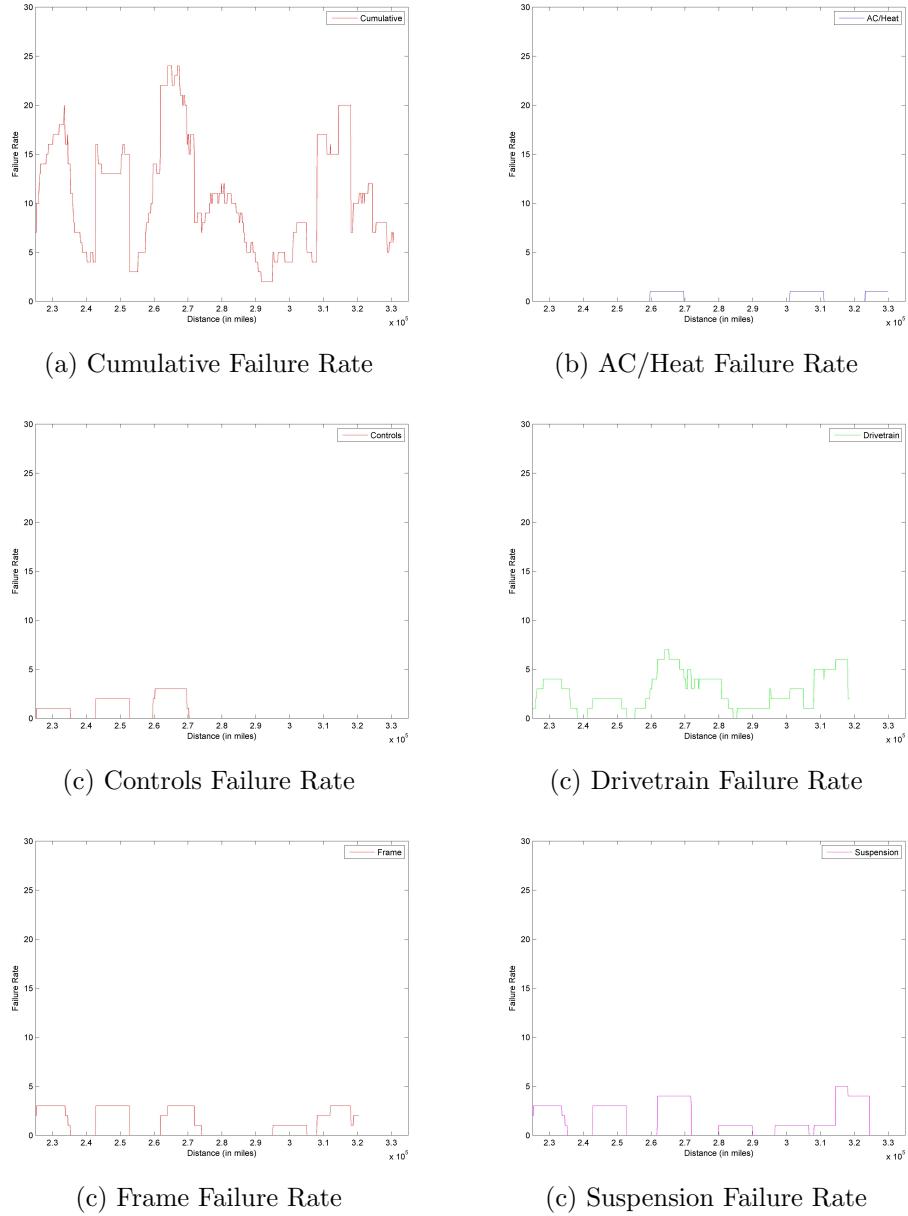


Figure 14 Subsystem Failure Rate Plots for Bus P5087.

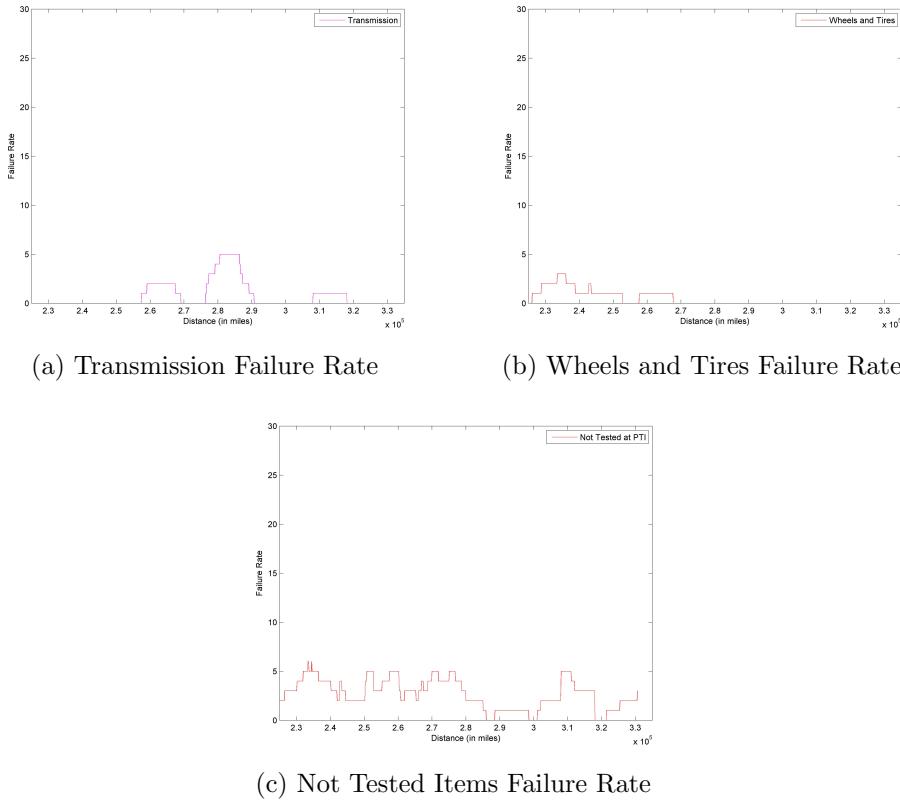


Figure 15 Additional Subsystem Failure Rate Plots For Bus P5087.

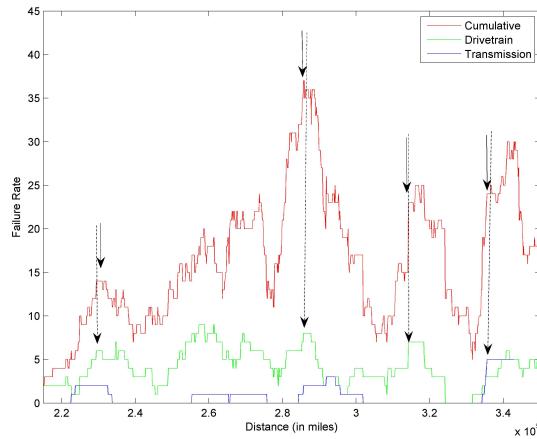


Figure 16 Bus P5001 Subsystem Failure Rates.

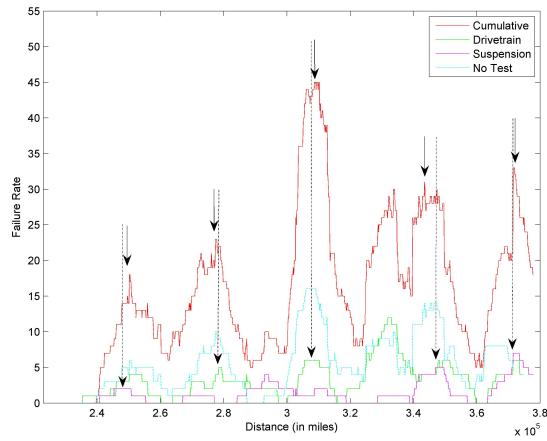


Figure 17 Bus P5003 Subsystem Failure Rates.

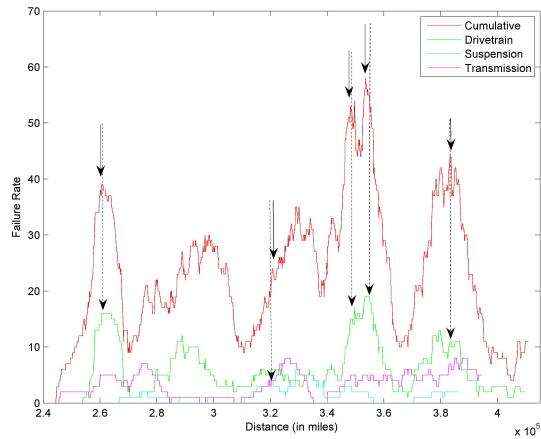


Figure 18 Bus L9414 Subsystem Failure Rates.

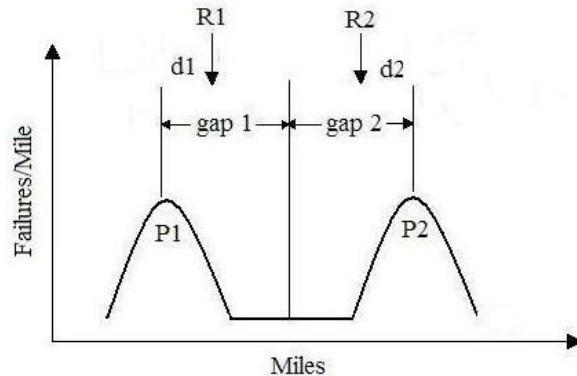


Figure 19 Failure Rate Peaks vs. Reported Failures.

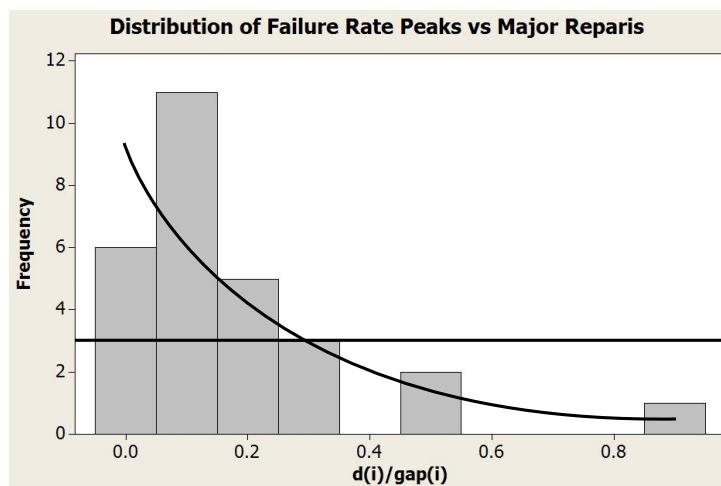


Figure 20 Distribution of Failure Rate Peaks vs. Reported Failures.