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USING ANECDOTAL INFORMATION TO MODEL THE AVAILABILITY OF AN EXISTING DYNAMOMETER SYSTEM

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ABSTRACT

Low-volume, custom-built or specialty equipment, by nature, has little statistically significant data to predict system availability over the equipment life. Their unique constructions are often costly to purchase and install, and are equally costly to maintain. This paper presents a practical method to estimate the availability of custom-built equipment, using a custom 4wd NVH dynamometer system as an example. The proposed method models the availability of an existing custom-built system using anecdotal component information based on interviews with field service personnel. The interview data is used to create estimated probability density functions for the major components of the system. Component probability density functions are assembled into a system model based on a derived system reliability function. This technique provides a low-cost, quick, model of system availability over time which can be used to assess the risk and cost effectiveness of system maintenance strategies.

1 INTRODUCTION

A large automotive manufacturer operates several specialty chassis dynamometers used in the development of new vehicle products. Due to the unique nature of these installations, it is difficult to predict the expected life or cost to maintain these systems based on statistically significant populations of like equipment. The purpose of this study is to recommend an economically feasible method to predict equipment availability of this custom equipment.

Between 1987 and 1992, five custom dynamometer systems were installed in the Noise, Vibration and Harshness (NVH) Laboratory of a large automotive manufacturer. Recent problems with the control system of the oldest dyno led to an increasing amount of downtime for the unit, and a reduction in system availability to about 95%. The laboratory must decide whether to continue making minimal repairs to this dyno, do a major overhaul, or replace the dyno completely to achieve a desired availability of 99%. The primary support for this decision is the projected system availability and cost to maintain the dyno system over the next ten years as provided by this study.

2 APPROACH

Due to the unique configuration of the NVH dyno system, statistically valid data for the entire system is not available. The major component parts, however, are common to most dyno applications and have more predictable failure modes and distributions. Thus, the approach used in this study is to develop a predicted system availability based on the combination of its derived component availabilities. This process is similar to the method of assessing system reliability based on the reliability of its components.

The major dyno components are standard production parts combined in a unique manner for a dynamometer application. There are no statistical data available for these individual components when exposed to dynamometer usage; but according to the equipment manufacturer's service technicians, each component has a predictable service life for the NVH application (Kuipers and Smith 2005). The approach in this study is to derive a probability density function for each of the major components based on anecdotal information provided by field service technicians. It is important to note that the accuracy of the resulting probability functions is directly related to the amount of experience for each technician interviewed, and their ability to describe their experiences.

Individual stochastic processes can be defined for each of the major components of the dynamometer system as a series of uptime activities characterized by a failure probability distribution and downtime activities characterized by a repair distribution. These processes are easily modeled using discrete event simulation, where a random number generator is used to estimate the durations of each component's uptime based on its probability density function. These individual durations are then assembled into an estimate of system availability for each time period using an Excel spreadsheet. Once the model is verified and validated, it can be used to evaluate the three scenarios: (1) minimal repairs to the dyno as each component fails, (2) major overhaul replacing the major components, or (3) replacing the entire dyno system.

3 EQUIPMENT AVAILABILITY

Availability is a measure of the probability that a repairable system, such as a dyno, will be operational at any given point in time *t*. This metric is of primary interest to the laboratory. Availability takes into account both the probability that the component will survive (reliability), and the probability that the component is restored to an operational state (maintainability). For example, if a lamp has 99% availability, there would be one time out of each 100 times a person switches it on that it will not light. The reason for the lamp not operating may be either a bulb failure, or that the bulb is in the process of being replaced. In general, availability *A* is defined as the percent of scheduled run time that the system is actually operational:

$$A_{dyno} = \frac{Uptime}{(Uptime + Downtime)} \qquad (1)$$

Downtime represents the entire time that the system is scheduled, but not operational. Modeled by the repair distribution, this activity contains more than just the repair time. The repair activity includes initial problem diagnosis by the dyno mechanic, lead time for service personnel to arrive, lead time for parts to arrive, actual repair time, system try-out and calibration.

4 MODELLING THE DYNO SYSTEM

The first step in predicting the system availability is to determine the primary function of the system and its associated “top failure mode”. It can be assumed that the availability of the system is driven by the component availabilities of those items most likely to cause the top failure for the system. The major components affecting system availability can be identified using fault-tree analysis, and are shown in the system block diagram (Figure 1).

4.1 Fault Tree Analysis

For this study, the fault-tree analysis was conducted by a team consisting of an experienced dyno mechanic, instrumentation and facilities specialists, dyno supplier representatives and the test engineer. The test engineer described the primary function of the dyno as providing a constant or accurate programmed load at the vehicle wheels. The accuracy specification was stated as +/- 5% of the target load in foot-pounds. Thus, the top failure mode is the inability to maintain the programmed load at the vehicle wheels within +/- 5% of target. The definition of failure for the NVH dyno application is unique. It is not possible to use absolute component failure data to model this requirement as a partial loss of function for a component may cause a failure of the system.

The fault-tree is developed by starting with the top failure mode and determining the major systems contributing to that failure. Sub-systems, components and sub-components causing the failure of the systems identified are established until a reasonable level of detail is accomplished.

Load applied by the dyno can be affected by any one of three subsystems: the control system, mechanical friction or safety shutdown (see Figure 2). The control system containing the processor, torque transducer and signal amplifier can affect load stability if a fault occurs in any one of its subcomponents. The mechanical friction of the system affects load when the combined friction of the components varies from the initial value determined during the calibration process. The safety system has thermal and ventilation sensors which monitor the DC Motor and cause the system to shut down when a fault is experienced. The reliability of the sensors themselves is not considered to be significant in this study.

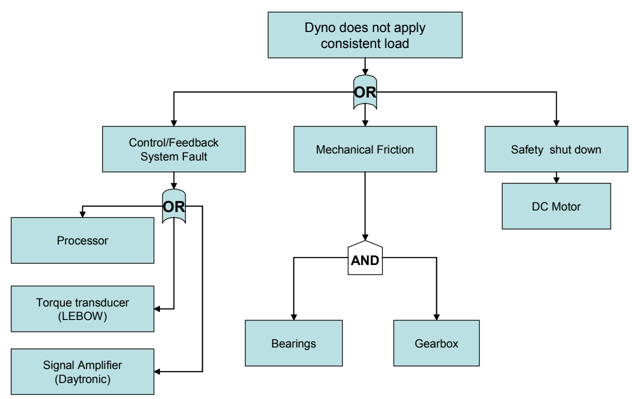

Figure 1: System Block Diagram for the Dyno

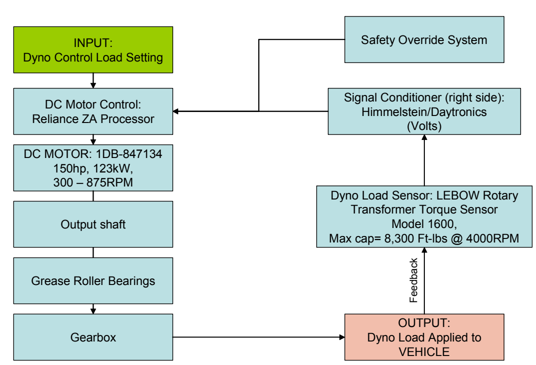

Figure 2: Failure Mode Fault Tree

After developing a detailed analysis of the systems and sub-systems driving the top failure mode, the fault-tree analysis is distilled into its major components. The resulting major components in this study are:

1. Processor (includes varistor drive unit),
2. 150HP DC motor,
3. Greased Roller Bearings,
4. Gearbox,
5. Load Sensor, and
6. Signal Amplifier.

4.2 Establishing System Availability

Once the relationships of the major components are established using fault-tree analysis, a mathematical model can be developed for the dyno system availability (Eberling 1997). A block diagram is used to model availability as shown in Figure 3. It is noted that the bearings, shaft and gearbox are modeled as parallel elements and the balance of the elements are in series. The block diagram for the probability of the inconsistent load failure P_f can be written as the following Boolean equation,

$$P_f = P_{processor} \cup P_{lebow} \cup P_{sigamp} \cup \left(P_{bearingt} \cap P_{gearbox}\right) \cup P_{motor}\,. \tag{2}$$

Assuming that inconsistent load failure is the primary failure mode for the system, the system availability A_{dyno} at any time t can be modeled as a function of the component availabilities,

$$A_{dyno}(t) = A_{processor} * A_{lebow} * A_{sigamp} * \left[1-\left(1-A_{bearing}\right)\left(1-A_{gearbox}\right)\right] * A_{motor}\,. \tag{3}$$

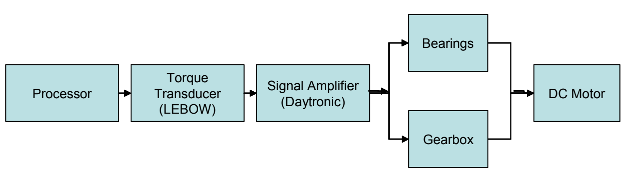

Figure 3: Availability Block Diagram

5 USING ANECDOTAL DATA TO ESTABLISH COMPONENT AVAILABILITY

Statistical data are not always easily available for reliability or availability of systems or components. Therefore, anecdotal information from field technicians experienced with the equipment is used to estimate the behavior of the component populations (Kuipers and Smith 2005). The anecdotal information is gained by conducting structured interviews with field technicians. The object of the interview process is to gain enough information to estimate a probability density curve to model each of the major components. The interview should include the following questions at a minimum:

A. At what age does the component begin to fail in the field?
B. How old were the oldest failed components found in the field?
C. At what age do most components fail in the field?
D. Does the component exhibit any unusual tendencies such as failures early in life, or are they relatively trouble-free until failure later in life?
E. If there are early failures with this component, approximately what percent of the population is affected?

Figure 4 shows how the minimum interview questions are used to construct a probability density curve.

It is important to clearly define the system failure mode when gathering anecdotal data because a complete component failure may not be required to produce the system failure defined. For instance, the DC motor used in the dyno system is also used in a wide variety of applications beyond that of a dyno drive. Although failure data on the component may be available from the motor manufacturer, this data would reflect the time to a complete failure as defined by the manufacturers specifications. The DC motor may drive inconsistent loads without completely failing the motor manufacturer specification. Thus the interview data can be more accurate than simple statistical component failure data when evaluating custom equipment.

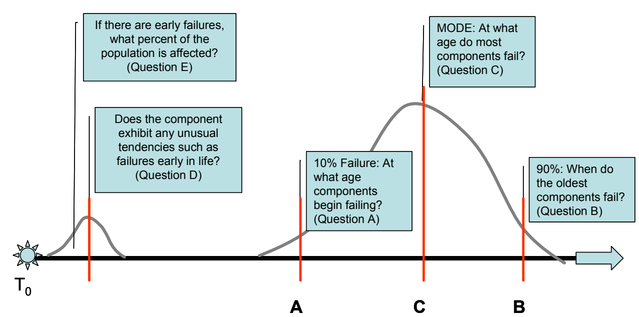

Figure 4: Anecdotal Data Is Used to Set Constraints for a Probability Density Curve

If there is no evidence of infant mortality in the component (Question D), the probability density curve is assumed to have a single mode value located at the age when most components fail (Question C). The mode value is then plotted on a timeline, along with the ages identified in Questions A and B. Since the field technician does not know the specific details of the component population failures, it must be assumed that failures will become noticeable to the field technician at a certain level of component cumulative distribution function probability (CDF). In this study, it is assumed that the technician will begin noticing field failures when a cumulative failure probability of 10% is reached. Thus, the age returned in answer to Question A can be assumed to occur at a CDF of 10%. Similarly, we assume that the technician recognizes the oldest failures (Question B) occur when the CDF has reached 90% . The point of trend recognition CDF= 10% and CDF=90% is an arbitrary assumption in this study which could benefit from further research.

Normal or Weibull distributions are recommended to characterize anecdotal data because they are easy to model and adapt well to qualitative data fitting. The Weibull distribution is particularly useful because it can be adapted to many different shapes by adjusting the beta value. The component failures can be modeled as either normal or Weibull distributions based on the position of the mode relative to the points A and B. If the mode is centered between points A and B, a normal distribution is assumed, otherwise, a Weibull model is used.

5.1 COMPONENTS WITH NORMAL DISTRIBUTIONS

The processor and gearbox components are assumed to have normal distributions. A normal distribution assumes a mean at point C which is equal to the mode (Question C). The standard deviation for the model is determined by working the inverse of the normal distribution calculation. Points A and B are both at a distance from the mean of the distribution such that the outlying tails each represent 10% of the population. Given, $\Phi(z) = 10\%$, z = 1.28 (from the normal probability table with 90% confidence). We also know that,

$$z = \frac{X - \mu}{\sigma} \tag{4}$$

where,

μ is the mean, point C, and

X is the average distance between point AC and CB.

Thus,

$$\sigma = \frac{0.5(AC + BC) - C}{1.28}. \tag{5}$$

For this study, the probability density function for each component failure is based on interviews with two dynamometer field technicians and the instrumentation and facility specialists included in the fault tree team

5.2 COMPONENTS WITH BIMODAL DISTRIBUTIONS

The DC Motor population could be modeled as a bimodal distribution because field data shows a significant difference between the life of motors that are maintained regularly, and those that are not. According the technicians, about 10% of all motors are not maintained and exhibit a normal failure distribution centered at 12 years of life. The balance of the motors survive to an average age of 18 years. Since the maintenance of the dyno system in this facility has been minimal, a normal distribution with a mean of 12 years is assumed in for this study.

5.3 COMPONENTS WITH SKEWED DISTRIBUTIONS

A skewed distribution, such as that of the roller bearings, is modeled with a Weibull distribution. To model the Weibull distribution, the characteristic life (theta) is assumed to be equal to the mode value C. The value for beta can be established using a Weibull modeling application such as Weibull Easy, or using a function in a spreadsheet program such as Excel. In this study, the scale value (beta) is indexed iteratively, using Excel, until the distribution results in 10% tail probabilities for the limit values A and B. The Excel Weibull function is shown below.

`WEIBULL( t, beta=?, theta, TRUE)` = 10% at the point that failures were first noticed (point A)

`WEIBULL( t, beta=?, theta, TRUE)` = 90% at the point when the oldest units failed (point B)

5.4 COMPONENTS WITH SKEWED BIMODAL DISTRIBUTIONS

The distributions of failures exhibiting Weibull bimodality are the most difficult to assess. In cases such as the torque transducer (Lebow unit) and signal conditioner, the field technicians relayed problems with infant mortality due to electrical failures. Further questioning established an estimated percentage of the population that failed early. The torque transducer component contains both an electrical angular speed sensor and a mechanical gearbox and bearing system. According to the technicians, the component demonstrate a small amount of early failures (about 5% of the population) in the first three years, usually in the first months of operation due to high levels of noise in the output signal. The balance of the components demonstrate a high level of reliability until wear-out failures occur at an average of 15 years; 90% of the torque transducers fail by the age of 19 years.

For the torque transducer, the two modes are considered separately to establish the value for beta. The description of the early failures is interpreted as an exponentialtype failure shape, with a beta value of 0.5. It is assumed that theta for this mode is three years or 12 quarters. The second distribution is assumed to have a characteristic life of 15 years. Thus the Excel function for the combined distribution is modeled as:

```
WEIBULL( t , beta = 0.5, theta= 12,TRUE)*0.05
+ WEIBULL( t , beta = ?, theta =
15,TRUE)*0.95 = 90% at the point when the
oldest units failed (point B)
```

The beta value for the second distribution is indexed until the cumulative probability of failure at 19 years is equal to 90%. This results in a beta value of 4.0 for the second mode of the distribution. The probability density distribution for the signal conditioner is established in a similar manner.

6 MODELLING THE AVAILABILITY OF THE SYSTEM

The performance of the complete system can be modeled using a simple simulation developed with an Excel spreadsheet (Banks, Carson, Nelson, and Nicol 2001). First, interval durations must be established for the analysis (quarterly for this study). The time to failure can be calculated based on a random number value applied to the component failure distribution. A random number generator is available as an Excel software function. The random numbers between zero and 1.0 relate directly to a point of cumulative failure probability in the life of a component, which in turn is used to calculate the time to failure for a component in each model iteration. It is important to use a separate random number calculation for each randomly derived component failure and subsequent repair down-time.

The time to failure for each component is then mapped to a timeline to indicate the time interval in which the failure occurred. The randomly derived repair down-time is then applied in the interval of failure. In some cases the actual repairs occur over a period of adjoining intervals, but for the purpose of this study, all downtime associated with a component failure was assumed to have occurred in the same quarter as the failure itself. For instance, a random number of 0.9 will result in a time to failure of 19 years, or 76 quarters, for the torque transducer in this study. Thus the downtime duration t_{repair} will be applied to the 76th quarter of life. The availability of the component in the 76th quarter is then calculated as,

$$A_{76} = t_{\text{int}\,erval} - t_{repair} = \frac{1 - t_{repair}}{t_{\text{int}\,erval}} \tag{6}$$

A new time zero is established in the following quarter (77th) and a new random number applied to determine the second failure of the component. In all cases, the components are assumed to be replaced with units "as good as new." Therefore, the shape of the probability density functions remains constant regardless of the number of component cycles. For the purpose of simplifying this study, repair times are assumed to be fixed values, based on historical downtime experienced upon each type of component failure.

Given the availability of each component, the system availability is calculated for each interval using the reliability block diagram relationship in Equation 3.

6.1 Model Verification and Validation

The simulation model is run for 100 cycles with each cycle modeling a 25-year period of dyno operation time to ensure stability. The coding of each component model is verified by comparing the model output component failure distribution to the estimated failure distribution function based on the anecdotal evidence. Table 3 (at the end of this paper), lists the components, the anecdotal data and the resulting estimated component failure distribution.

Validation of the model is challenging because there is only one dyno available with the same component configuration as the one modeled. To adequately prove out this method as a method for use in other applications, a population of models would need to be generated using this method, then each validated against the actual service history of the actual equipment (DaimlerChrysler 2005). Time and budget did not permit this type of thorough validation for this study; but the model did accurately predict failures experienced by the subject dynamometer. Table 1 below shows the service history for the actual dyno system as compared to the predicted results provided by the simulation. Most of the component failures experienced by the dyno are predicted with sufficient accuracy for the purpose of estimating the type of repair strategy needed. Even though the simulation has a tendency to predict an earlier failure than the actual, its accuracy is within a year and the risk of error is much greater if the failure is not predicted in enough time to respond to it. The signal amplifier component prediction is the only poor prediction; but it is clear from the failure distribution curve for this component that there is much variability in the component life, thus the discrepancy in the age is not considered a major problem with the simulation validity.

Table 1: Model Validity

Item	Actual Failure Experienced	Failure Predicted by this Simulation
Signal Amplifier	39	57
DC Motor	42	36
Gearbox, Bearings	49	47
Torque Transducer	73	61
Processor	75	68

6.2 Modeling Alternative Repair Actions to an Existing System:

Once the model is validated, it can be run for the three scenario conditions: Minimal repair, overhaul and complete system replacement. Prior to running the simulation for each of these conditions, the model is tuned to reflect the actual failures experienced by the subject dyno system. This is done by starting the probability density clock at the quarter immediately after the most recent of each actual component failure. The area of focus for this study is the predicting behavior of the dyno system over the next ten years (2005 – 2015). Figure 5 shows the compared average interval availabilities for each of the three conditions evaluated. The first condition evaluated is to provide minimal repair to the system, replacing major components only as they fail. This is modeled by the basic simulation model described above, in which the components are replaced in the quarter of failure with "good as new" parts. The projected average interval availability for this period is estimated as 99.13%.

For the overhaul condition, the simulation model used in the minimal repair assessment is modified to show the processor and torque transducer renewed by the 1st quarter in 2006. In addition, review of the existing system with the supplier revealed an opportunity to eliminate the gearbox in the system if a second motor was installed (e.g., one motor to drive each dyno axle). Thus the gearbox component was modeled as removed during the overhaul, and a new AC motor was added as a new major component in the simulation. It was noted that the feedback system for the second motor consists of a solid state load cell device which is much more reliable than the torque transducer used on the existing DC motor. Due to the high reliability of the load cell, it was considered as part of the AC motor. The AC motor also exhibits a 20% longer life expectancy than that of the DC motor. The resulting average availability for the next ten years is estimated as 99.76%.

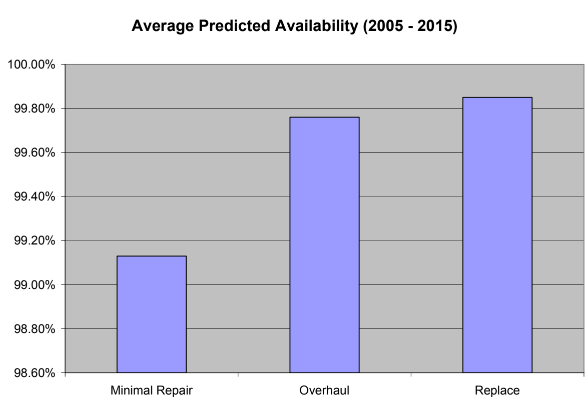

Figure 5: Modeled Availabilities of the Three Conditions

A complete system replacement is modeled as a unit with two independent AC motors driving the rolls and replacement of the shaft and bearings. No replacement of major components is expected before 2015 with this alternative and the average interval availability is estimated as 99.85%.

7 CONCLUSION

There is a clear improvement in system availability as more components are involved in the repair. The replacement of the complete system is shown, as expected, to provide the most improvement in availability at 99.85%. A trivial decision could be made based only on the alternative that provides the highest average interval availability, to replace the system.

For this problem however, the economic cost versus benefit must be considered to make a cost effective decision. All of the alternatives meet the facility owner's requirement of over 99% availability for the system. Therefore the question is, which alternative provides the most increase in availability for the dollars spent.

Using the simulation models for each of the three alternatives, a total amount of projected downtime can be determined. This downtime includes the time for conducting the initial repair action and subsequent repair events over the ten-year period. The cost of the downtime includes considerations of costs for idle personnel, as well as the cost of testing at an alternative site during repair. It is important to note that the minimal repair option results in unscheduled downtime, which is more costly to manage and has a greater chance of customer loss. For this reason, it is assumed that the cost of downtime for the minimal repair option was twice that of the other options.

The cost of the initial action (or capital project acquisition) is added to the project cost of downtime to return a gross cost of operating the system under each alternative. The Cost per % increase in average interval availability is calculated,

$$Cost_{\%increaseinavalability} = \frac{C_a + C_i + C_{interval} + C_{unscheduled}}{A_{acheieved} - A_o} \qquad (7)$$

where,

C_a = the cost of capital equipment acquisition,

C_i = the cost of equipment installation and set-up,

$C_{internal}$ = the cost of idle personnel and facility,

$C_{substitution}$ = the cost to substitute another facility during repairs,

$C_{unscheduled}$ = the cost of rescheduled tests due to unexpected downtime at alternative facilities which may include premium labor, and potential customer loss,

$A_{achieved}$ = the resulting interval availability for the ten years from 2005 to 2015,

A_o = 95.1% original availability from quarters 67 and 68.

The cost versus benefit analysis reveals the best response to the dynamometer issue is to conduct a major overhaul of the system (but not completely replace it). This is evidenced by the lower cost per unit of availability improvement and is the recommended course of action as shown in Table 2 below.

Table 2: Cost Analysis Results

Alternative	Projected Avg Availability	Projected Downtime after Renewal Action (days)	Cost per % Increase in Availability
Minimal	99.13%	31.76	$ 25,332.48
Overhaul	99.76%	8.76	$ 21,353.43
Replace	99.85%	5.47	$ 30,434.78

The system availability model based on anecdotally derived estimates of the component failures does an effective job of distinguishing the predicted performance differences of the alternatives considered in this study. The system is scheduled for overhaul in December 2006.

7.1 Suggestions for Further Research

The heuristics associated with this modeling method were developed specifically for use in characterizing dynamometer component availability, but have the potential to be applied to other systems. There are two major areas that could benefit from further study to make this application a good tool for diverse applications - investigate the characteristics and limitations of using anecdotal data, and determine the efficacy of this method in predicting the response of other types of equipment or systems.

The study of the characteristics and limitations of anecdotal data should include: (1) analysis of the effectiveness of the standard questions (i.e., can the questions for further optimized and standardized?), (2) how can technician experience be qualified to provide consistent results and (3) refinement of interpreting questionnaire results into probability density curves for component failure. In particular, further work is required to establish the number of cumulative field failures a technician experiences before it is perceived as an indicator of the behavior of the population. In this study, it is assumed that a 10% actual component failure rate must exist before a technician perceives a problem with the product. Correspondingly, it is assumed that 10% of the population had yet to fail at the point that the technician considers the oldest units fail. Once the method for collecting anecdotal data is optimized, further study would be in order to identify applications which respond best to this method.

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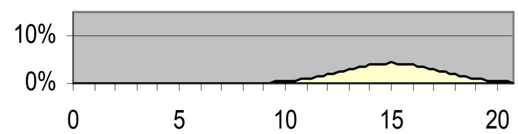
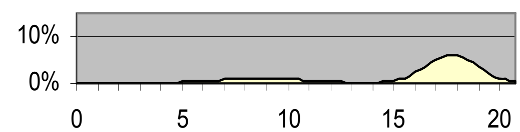
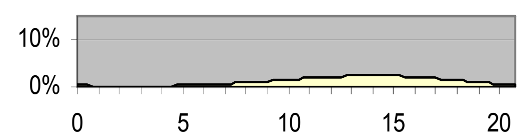
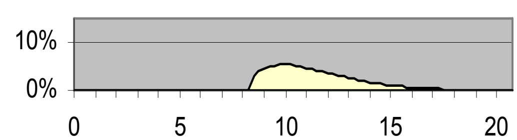
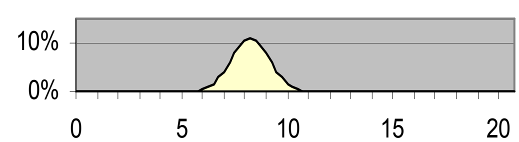
Table 3: Failure Distribution Curves Derived from Anecdotal Data for Dynamometer Components.

Component	**Failure Data Based on Interview with Field Service Tech**	**Plot of Estimated Failure Distribution** (percent of population failing each year)
Processor	**Normal Dist** Mean = 12.0 years σ = 2.34 years	
DC Motor	**Bi-Modal Dist** Mean1 = 12 years for population not maintained motors (10%) Mean2 = 18 years population of maintained motors (90%) Total Mean = 16.8 years σ = 2.34 years	
Torque Transducer	**Combined Weibull Dist** θ = 3.0 years, β= 0.5 population experiencing infant mortality (5%) θ = 12.0 years, β > 4.0 for balance of population failing by 15 years (95%)	
Grease-Type Roller Bearings	**Minimum Life Weibull Dist** θ = 12.0 years 10% of population fails by 10 years, 90% fail by 15 years	
Gearbox	10 year max design life with wide variation due to maintenance. No data, therefore assume **Normal Dist** with 5% reliability at 10 years. Mean = 8.5 years σ = 0.9 years	
Signal Conditioner	**Combined Weibull Dist** θ = 1.0 years, β= 0.5 population experiencing infant mortality due to high signal noise (25%) θ = 12.0 years, β > 4.0 for balance of population failing by 17 years, with 35% failing by 10 years (95%)