

## Extracting Information from Field-Failure and Warranty Data Bases: An Important Opportunity

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Based on work being done jointly with Luis A. Escobar (LSU), Tim Davis (Ford), Huaqing Wu (ISU), and ISU graduate students Ed Staats and Kimberly Wentzlaff.

Several companies have provided motivation, data, and support for this work.

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## Extracting Information from Field-Failure and Warranty Data Bases: An Important Opportunity Overview

- Discuss important applications involving field/warranty data
- Previous work
- Indicate some general difficulties with field/warranty data
- Progress in developing methods for the applications
- Examples
- Additional issues and possible solutions

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## Reliability in the Commercial Sector

- Up-front **Design for Reliability** is critical in today's commercial manufacturing environment
- Why Use Warranty/Fleet Maintenance Data?
  - ▶ Contains useful information.
  - ▶ Reflects direct customer experience with product.
  - ▶ Warranty data are almost free.
  - ▶ Close the loop.

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## Important Applications Involving Warranty and Fleet Maintenance Data

1. **Financial:** Predict future warranty or maintenance costs
2. **Cost reduction:** Early detection and correction of unanticipated reliability problems.
3. **Transfer function between lab tests and field performance:**
  - Resolve discrepancies to improve test procedures or better understand reasons to lack of agreement.
  - Provide stronger basis of extrapolation of future lab tests to predict field performance.
4. **Reliability improvement:** Feed subsystem and component-level reliability information back to design engineers to improve future generations of product.

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## Some Previous Work

There has been a considerable amount of previous work done in the area of field reliability data analysis. For example:

- Kalbfleisch, J.D., Lawless, J.F., and Robinson, J. A. (1991). Methods for the Analysis and Prediction of Warranty Claims. *Technometrics*, 33(3), 273–285.
- Kalbfleisch, J.D. and Lawless, J.F. (1988). Estimation of Reliability in Field-Performance Studies. *Technometrics*, 30(4), 365–378.
- Lawless, J.F. (1998). Statistical Analysis of Product Warranty Data. *International Statistical Review*, 66(1), 41–60.
- Robinson, J.A. , and McDonald, G.C. (1991). "Issues Related to Field Reliability and Warranty Data," in *Data Quality Control: Theory and Pragmatics*, eds. G.E. Liepins and V.R.R. Uppuluri, Marcel Dekker, Inc, 69–89.

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## Some Difficulties with Warranty Data

- Warranty data are often **contaminated** with missing values, errors in reporting, delays in reporting, or even fraud.
- Amount of product **use** (e.g., cycles) is often the best time scale to measure product life, but amount of **calendar** time is often all that is reported.
- Environmental characterization (including use-rate, stresses, etc.) is generally uncertain or altogether unknown (smart sensors in some up-coming products may provide better information in the future, at least on a sample of units in service).
- Failures reported for units that fail under warranty.
  - ▶ Data are reliable only until the end of the warranty period.
  - ▶ Status of unfailed units may be unknown (including retired units or units never put into service).

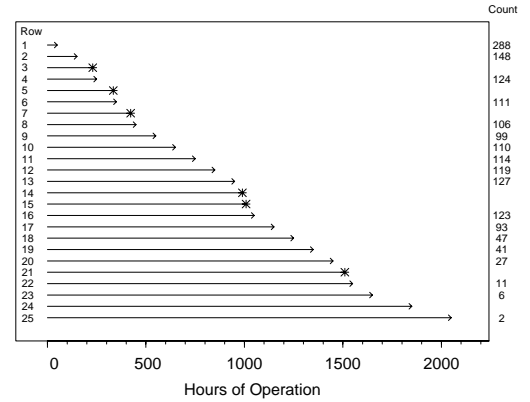
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### Comments on Data Needs

- Most field failure data are obtained from “repairable systems.”
- To effectively improve reliability, it is necessary to get information from systems at or close to the replaceable-unit level/failure mode.
- For many purposes, it is important to keep track of potentially important explanatory variables (date of manufacture, date of sale, operating environment, etc.)
- Need information on surviving units as well as failed units.
- With appropriate modeling, replaceable-unit level/failure mode data can often be analyzed under a simple illuminating iid model.
- In other cases, point process models can be useful.

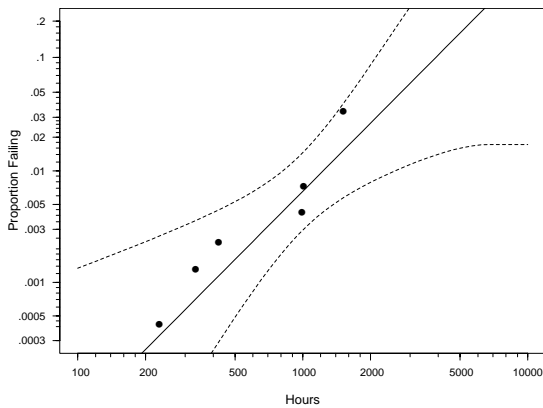
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### Jet Engine Bearing Cage Field Failure Data (from the 1983 USAF “Weibull Handbook”)



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### Weibull Probability Plot of the Bearing Cage Field Failure Data



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### Special Features of Automobile Warranty Data (may also arise in other products)

- In the US, automobile companies use a two-dimensional (time and miles) warranty, which results in two-dimensional censoring (typically 36 months in service or 36 thousand miles for most components in the automobile).
- Only limited information on exact cause of report or failure (e.g., **labor code** and a cost are recorded).
- Good information on date of sale and date of manufacture.
- With data from many **labor codes**, there is useful information about use-rate distribution (e.g., miles per year) in the entire data base for a particular type of automobile.
- Potential biases in estimation (e.g., high use-rate units may have a different cycles-to-failure distribution or high-speed drivers may have a different miles-to-failure distribution).

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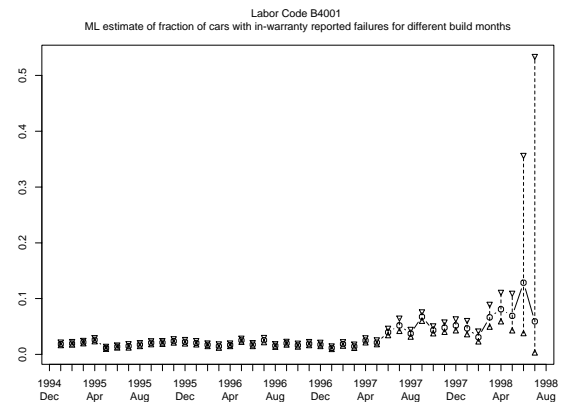
### Application 1 Early Detection Using Reliability Statistics

Generalization of the classical process monitoring, control chart, change-point problems:

- Data for a particular labor code and manufacturing period arrive over time.
- Data can be viewed as censored failure times or counts from a mixture of distributions.
- An appropriate detection rule will probably depend on the updated empirical cdf at each data-inspect point, for each manufacturing period (time increment for data-inspect points probably monthly or weekly).
- Detection needs to be automatic with with some reasonably small false alarm rate.

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### Retrospective View of Estimates of Fraction Failing Under Warranty for Labor Code B4001



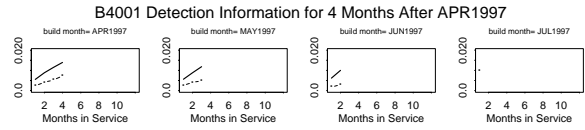
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**Example—Early Detection of a Problem Arising from a Cost-Reduction Design Change in a Product**

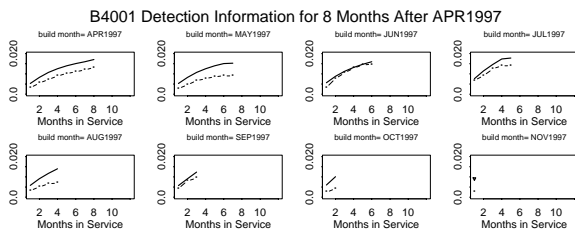
Specific characteristics:

- Variable delay between manufacturing and introduction into service (results in multiple censoring).
- Variable number of units produced per month (approx 10,000/month).
- Manufacturing periods divided into months.
- Data reviewed for possible detection every month.
- Have a standard cdf for comparison (based on previous history with the same labor code).

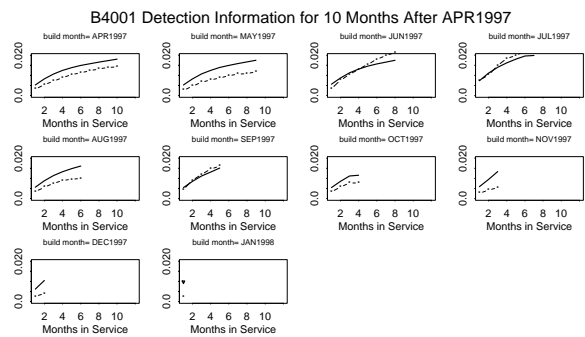
**B4001 Build Months April 1997-July 1997  
Data In August 1997**



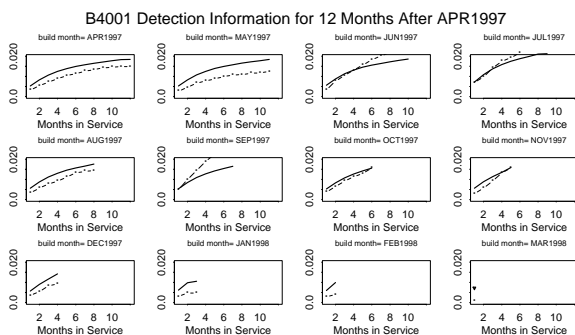
**B4001 Build Months April 1997-November 1997  
Data In December 1997**



**B4001 Build Months April 1997-January 1998  
Data In February 1998**



**B4001 Build Months April 1997-March 1998  
Data In April 1998**



**Possible Detection Rules**

Consider the deviation between a base-line (historical) fraction failing  $F_t^*$  and observed fraction failing  $\hat{F}_t$ , over period of observation. Signal if

- The cumulative number of failures for a given production period/number of months in service exceeds a specified limit.
- The estimated fraction failing for a given production period/number of months in service exceeds a specified limit, viz.

$$g(\hat{F}_t) > g(F_t^*) + k_t^C se_{g(\hat{F}_t)}^* \quad \text{or}$$

$$g(\hat{F}_t) - g(\hat{F}_{t-1}) > [g(F_t^*) - g(F_{t-1}^*)] + k_t^I se_{[g(F_t^*) - g(F_{t-1}^*)]}^*$$

where  $g$  is an appropriate function like the logit.

### How to Choose Critical Values

- Need to control the false alarm rate.
- Need to decide where to allocate power.
- Sampling distribution of the critical statistic(s)
  - ▶ exact distribution
  - ▶ large-sample approximation
  - ▶ simulation-based approximation
- Tune the decision rule(s) using historical data on the complete data base, across many **labor codes**.

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### Application 2 Prediction of Future Warranty or Fleet Maintenance Costs

- Predictions are required for
  - ▶ Financial reporting and establishing appropriate amount of warranty reserves
  - ▶ Product warranty costing
  - ▶ Pricing service contracts
- Traditional methods of forecasting (e.g., time series) are often inadequate. In many areas of application, warranty cost forecasts are consistently too low.

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### Example of Predicting Future Warranty Cost

- Cars enter service throughout the year (staggered entry)

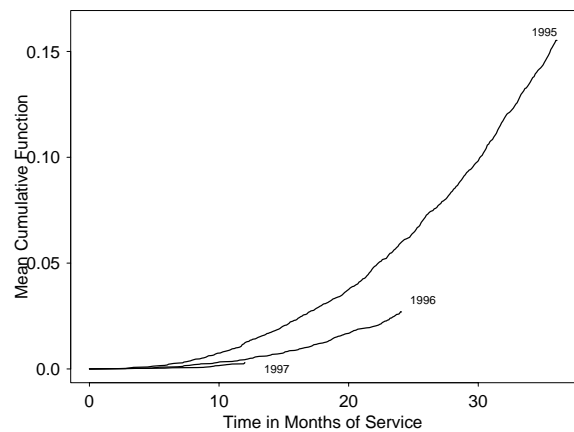
Group	Model Year	Number
1	1995	$n_1 = 11,345$
2	1996	$n_2 = 13,389$
3	1997	$n_3 = 14,296$

- **Objective:** Monthly forecast of future warranty costs using available past warranty data.

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### Data at September 1998

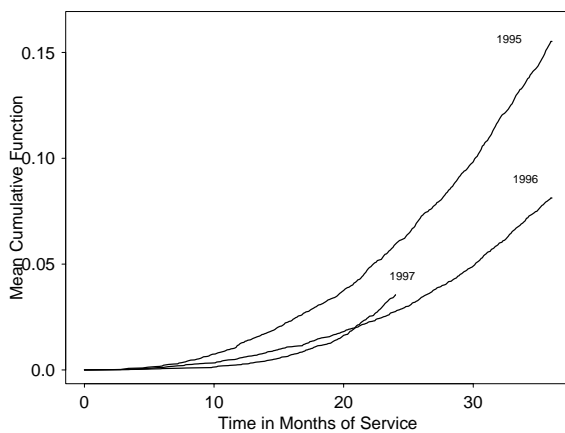
Mean Cumulative Function for Automobile Failures



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### Data at September 1999

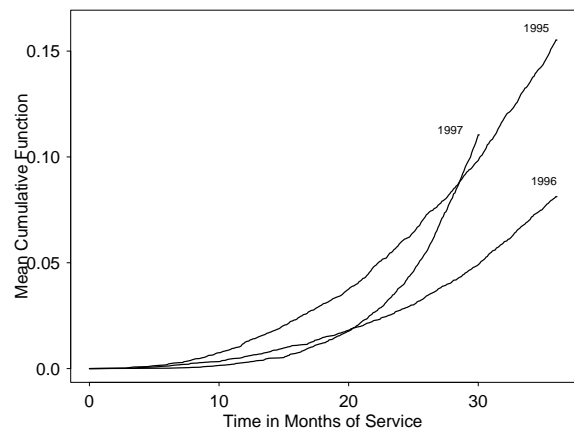
Mean Cumulative Function for Automobile Failures



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### Data at March 2000

Mean Cumulative Function for Automobile Failures



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### Proposed Method for Predicting Future Warranty Costs

- Use statistical modeling to determine the causes of previous under forecasts (we expect that under-forecasts are caused by **special-cause** failures)
- Disaggregate **special-cause** failure costs from **common-cause** failure costs.
- For the sake of computational efficiency, could use traditional methods to predict **common-cause** failure costs.
- Use reliability model-based methods to predict **special-cause** failure costs.

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### Example of Predicting Future Warranty Cost-Continued

- **Common-cause** modeled with Non Homogeneous Poisson Process (NHPP) with **proportional recurrence rates**  $\nu_i(t)$ , for each model-year, i.e.,

$$\begin{aligned}\nu_2(t) &= k_2 \nu_1(t) \\ \nu_3(t) &= k_3 \nu_1(t)\end{aligned}$$

- With the power-model recurrence rate this implies

$$\nu_i(t) = \frac{\beta}{\eta_i} \left( \frac{t}{\eta_i} \right)^{\beta-1}, \quad i = 1, 2, 3$$

the shape parameter  $\beta$  is common for the three groups.

- **Special-causes** of failure are forecasted separately using reliability methods and they are added to the common-causes forecast.
- The recurrence rate for group  $i$  is  $\nu_i(t) + m_i(t)$ , where  $m_i(t)$  is the recurrence rate for identified special-causes.

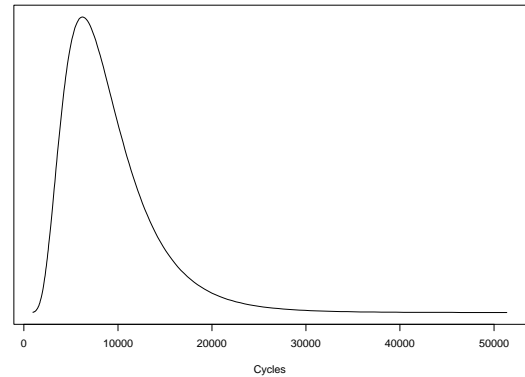
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### Application 3 Establish a Transfer Function Between Laboratory Tests and Field Performance

- Laboratory tests measure life in units of test cycles or test time.
- Laboratory tests are typically **accelerated**.
- A model (e.g., a degradation model) is needed to link accelerated test time to actual use life time:
  - ▶ Effect of acceleration
  - ▶ Distribution of environmental conditions
  - ▶ Distribution of use-rates in actual use
- With a **complete** failure time model and knowledge of use environment (stresses, use-rate distributions, etc.) can relate laboratory data and field performance.

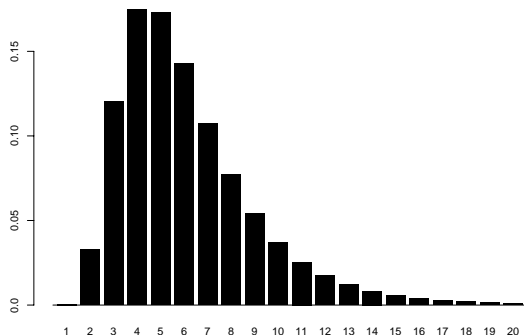
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### Component-A Laboratory Test Cycles to Failure



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### Appliance Use-Rate Distribution



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### Example Use-Rate Model

- Life of a component in cycles of use, has a distribution

$$F_C(c) = P(C \leq c) = \Phi \left[ \frac{\log(c) - \mu}{\sigma} \right]$$

- Actual use-rate has a distribution given by the proportion of users  $\pi_i$  ( $i = 1, \dots, k$ ) that use the appliance at constant rate  $R_i$ , where  $\sum_{i=1}^k \pi_i = 1$ .

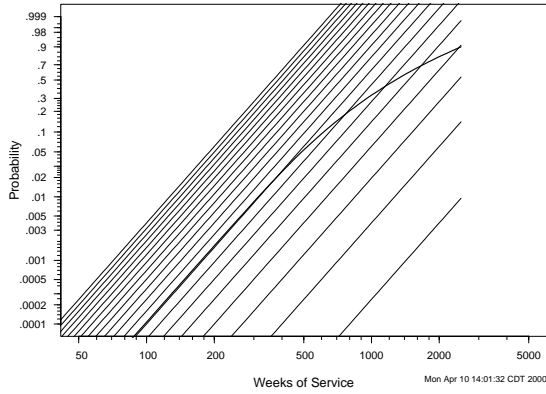
- Then the failure probability as a function of time is

$$F_T(t; \theta) = P(T \leq t) = \sum_{i=1}^k \pi_i \Phi \left[ \frac{\log(t) - \mu_i}{\sigma} \right]$$

where  $\theta = (\mu_1, \dots, \mu_k, \sigma)$  and  $\mu_i = \mu - \log(R_i)$ .

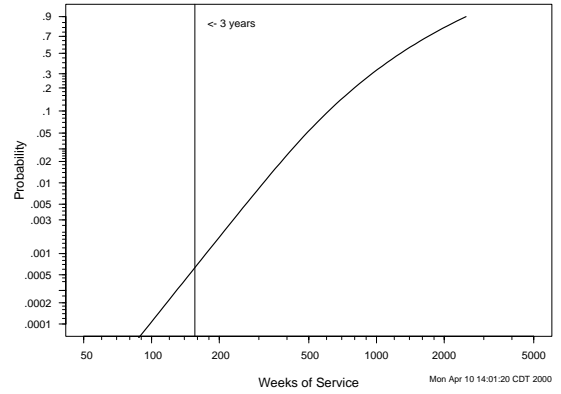
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**Predicted Field Reliability of Component-A  
as a Weighted Average**



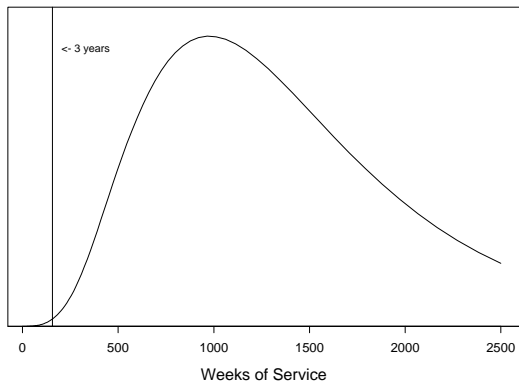
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**Component-A  
Prediction of Fraction Failing in the Field**



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**Component-A  
Predicted Density of Failures in the Field**



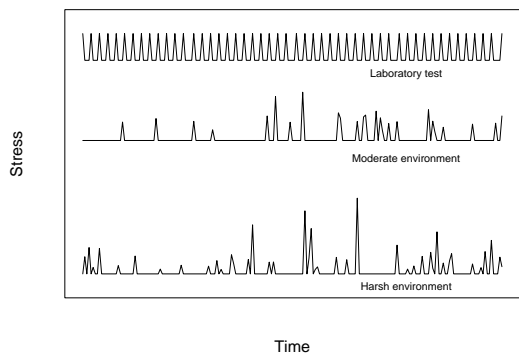
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**Comments on the Predicted Failure Probability  $F_T(t; \theta)$**

- The failure probability for the population  $F_T(t; \theta)$  is a mixture or weighted average of failure probabilities a constant rate.
- In general,  $F_T(t; \theta)$  is not a simple distribution, but for some certain ranges of  $t$  it may be well approximated by a simple distribution (Weibull, lognormal, etc.)
- Disagreement between  $F_T(t; \theta)$  and product field performance requires careful study of the source of the disagreement.
- Agreement between  $F_T(t; \theta)$  and field reliability indicates that laboratory testing is useful for predicting future field performance.

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**Comparison of Stress Profiles for Laboratory Testing  
and Field Use**



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**Environmental/Use-Rate Characterization**

- Generally, use-rate and environmental characterization are important.
- Difficult to obtain for individual units.
- External statistical/population information (e.g., from marketing surveys) may be available and useful.
- Emerging opportunity: smart chips in some products.

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### Additional Issues and Possible Solutions

- Seasonality in use-rate or environmental stresses [model seasonality to determine the base-line  $F^*(t)$ ].
- Beginning of service time often unknown for units that did not fail (estimate distribution of time to enter service from those that did fail).
- Some units may be retired while still under warranty (obtain information on the distribution of time to retire)
- Units may have multiple time scales affecting life (e.g., amount of running time, amount of real time, and number of startups).
- Good failure time data available only until the end of the warranty period, but customers are sensitive to reliability problems even after the warranty period ends. (Track an approximately **unbiased subset** beyond the warranty period).

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### Potential to Improve the Quality of the Data in Warranty and Fleet Maintenance Data Bases

- Warranty data bases generally exist for financial reporting purposes, not for engineering feedback.
- Changes being implemented to improve reporting speed and accuracy.
- Perhaps opportunity to improve information needed for engineering evaluation (e.g., better information on cause of failure).

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### Concluding Remarks

- Warranty and fleet maintenance data bases contain useful information.
- Field data are messy, and special tool, models and, in some cases, external information is needed to extract the useful information.
- Once procedures for using data have been established, using those procedures is relatively inexpensive.

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