CHAPTER 5. PROBABILISTIC ENGINEERING ANALYSIS – TIME-DEPENDENT PERFORMANCE

In the previous chapter, methods were examined for obtaining the system's reliability function analytically or computationally. In the calculation of probability values, we consider time independent safety events. However, in many practical cases, system's performance degrade over time. In this chapter, time dependency in the probability of safety occurrence (or reliability) will be introduced. We will develop the reliability models necessary to observe the reliability over the life of the system, instead of at just one point in time. In addition, performance measure such as MTTF and failure rate are presented and also its related distributions are introduced. An accelerated life test will be discussed to acquire time dependent data in an efficient manner. Lastly, we take a glance at overview of PHM in the end of the chapter.

5.1 Reliability Function (Time-Dependent)

5.1.1 Reliability Function

The **Reliability Function** $R(t)$, also known as the **Survival Function** $S(t)$, is defined by:

$R(t) = S(t)$ = the probability a unit survives beyond a designed life t.

Since a unit either fails or survives, one of these two mutually exclusive alternatives must occur as

$$\begin{aligned} R(t) &= P(T > t) = 1 - P(T \le t) = 1 - F_T(t) \\ &= 1 - \int_0^t f_T(\tau)d\tau = \int_t^\infty f_T(\tau)d\tau \end{aligned} \tag{59}$$

where T is a time-to-failure, $F_T(t)$ is the probability distribution function or CDF of an actual life, and $f_T(t)$ is the PDF of an actual life.

5.1.2Expected Life or Mean Time-To-Failure (MTTF):

$$\begin{aligned} E[T] &= \int_0^\infty \tau f_T(\tau)d\tau = -\int_0^\infty \tau \frac{\partial R(\tau)}{\partial \tau} d\tau \\ &= -\left[tR(t)\right]_0^\infty + \int_0^\infty R(\tau)d\tau \\ &= \int_0^\infty R(\tau)d\tau \end{aligned} \tag{60}$$

5.1.3 Failure Rate (or Hazard Function):

Insight is normally gained into failure mechanisms by examining the behavior of the failure rate. The failure rate, $h(t)$, may be defined in terms of the reliability or the PDF of the time-to-failure (TTF). Let $h(t)\Delta t$ be the probability that the system will fail at some time $T < t + \Delta t$ given that it has not yet failed at $T = t$. Thus, it is the conditional probability as

$$
\begin{aligned}
h(t)\Delta t &= P\{T < t+\Delta t \mid T > t\} = \frac{P\{(T>t)\cap(T<t+\Delta t)\}}{P\{T>t\}} \\
&= \frac{P\{t<T<t+\Delta t\}}{R(t)} = \frac{f_T(t)\Delta t}{R(t)} \\
&\text{or} \\
h(t) &= \frac{f_T(t)}{R(t)}
\end{aligned}
\tag{61}
$$

There are a handful of parametric models that have successfully served as population models for failure times (TTF) arising from a wide range of products and failure mechanisms. Sometimes there are probabilistic arguments based on the physics of the failure mechanics that tend to justify the choice of model. Other times the model is used solely because of its empirical success in fitting actual failure data.

5.1.4 Bathtub Curve:

The bathtub curve is widely used in reliability engineering, although the general concept is also applicable to humans. It describes a particular form of the hazard function which comprises three parts:

- The first part is a decreasing failure rate, known as early failures or infant mortality.
- The second part is a constant failure rate, known as random failures.
- The third part is an increasing failure rate, known as wear-out failures.

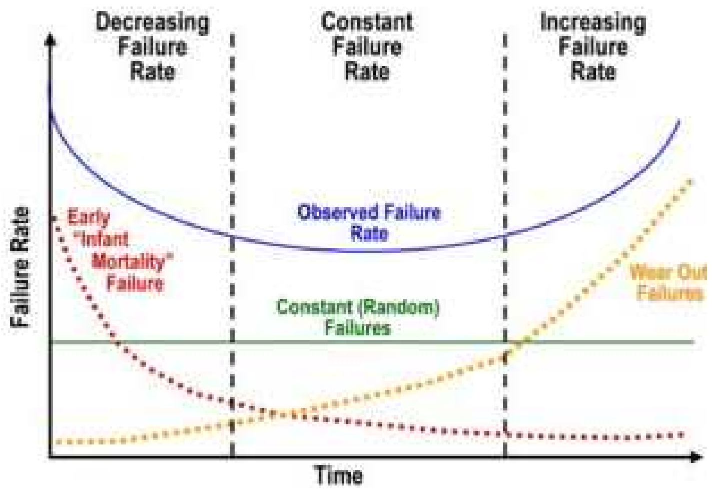


Figure 5.1: Bathtub Curve for Hazard Function (or Failure Rate)

Homework 16: *Failure testing*
Perform the failure testing of a paper clip as instructed.

5.2 Parametric Distribution for Life Data

Some parametric models will be described in this section. There are two classes to describe a failure rate: (1) constant failure rate (section 4.4.1) and (2) time-dependent failure rate (sections 4.4.2-4.4.4).

5.2.1 Exponential Distribution (Constant Failure Rate)

The exponential model, with only one unknown parameter, is the simplest of all life distribution models.

PDF:

$$f_T(t;\lambda) = \begin{cases} \lambda e^{-\lambda t} & , \quad t \ge 0 \\ 0 & , \quad t < 0 \end{cases}$$

where $\lambda > 0$ is a rate parameter of the distribution.

CDF:

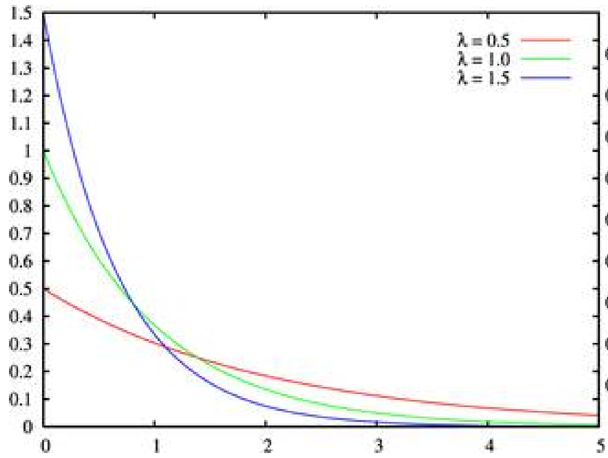
$$F_T(t;\lambda) = \begin{cases} 1 - e^{-\lambda t} & , \quad t \ge 0 \\ 0 & , \quad t < 0 \end{cases}$$

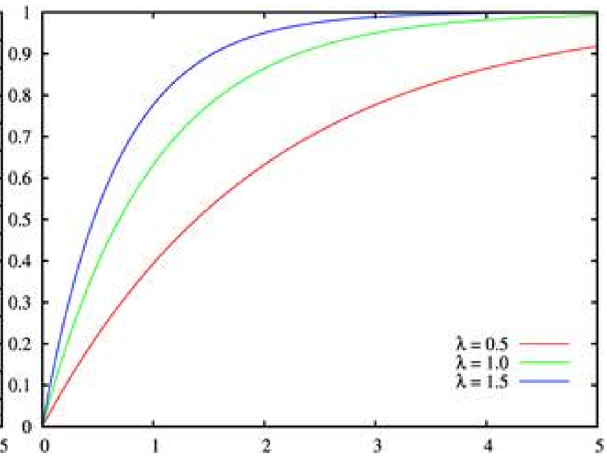
Reliability and Hazard Functions:

$$R(t) = 1 - \int_0^t f_T(\tau)d\tau = e^{-\lambda t} \quad \text{and} \quad h(t) = \frac{f_T(t)}{R(t)} = \lambda$$

MTTF:

$$\text{MTTF} = \mu_T = \int_0^\infty \tau f_T(\tau)d\tau = 1/\lambda \qquad \text{and} \qquad \sigma_T^2 = 1/\lambda^2$$





(a) PDF (b) CDF

Figure 5.2: Exponential Distribution

5.2.2 Weibull Distribution

PDF:

$$f_T(t;k,\lambda,a)=\frac{k-a}{\lambda-a}\left(\frac{t-a}{\lambda-a}\right)^{k-1}e^{-\left(\frac{t-a}{\lambda-a}\right)^k}$$

where $t \ge a$, a is a waiting time parameter, $k>0$ is a shape parameter, and $\lambda>0$ is the scale parameter of the distribution.

CDF:

$$F_T(t;\lambda)=1-\exp\left[-(t/\lambda)^k\right]$$

Reliability and Hazard Functions:

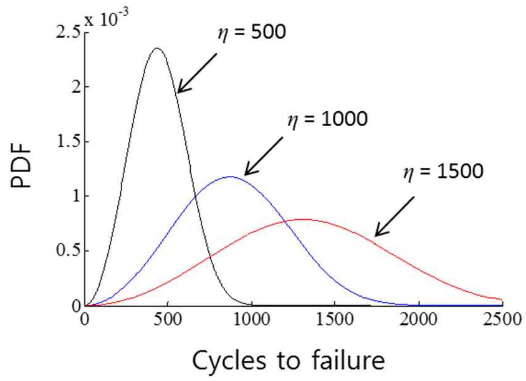
$$R(t)=1-\int_0^t f_T(\tau)d\tau=\exp\left[-(t/\lambda)^k\right] \quad \text{and} \quad h(t)=\frac{k}{\lambda}\left(\frac{t}{\lambda}\right)^{k-1}$$

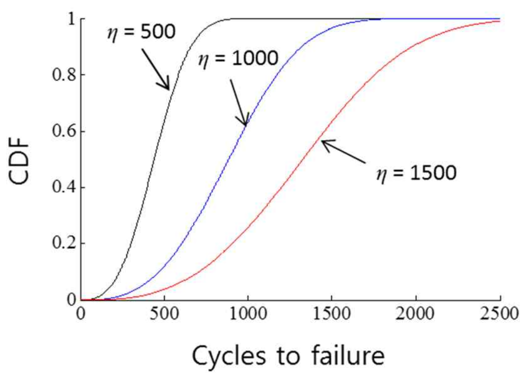
MTTF:

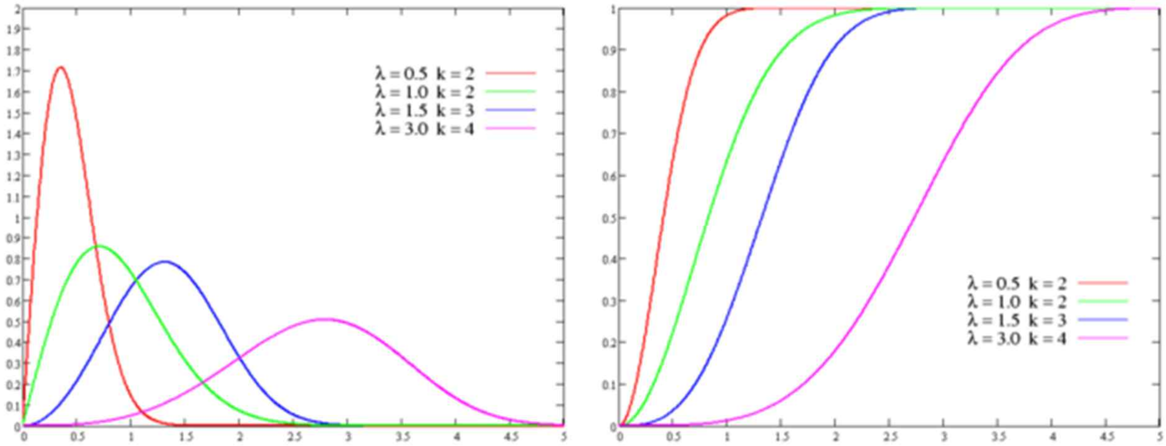
$$\text{MTTF}=\mu_T=\int_0^\infty \tau f_T(\tau)d\tau=\lambda\Gamma\left(1+\frac{1}{k}\right) \quad \text{and} \quad \sigma_T^2=\lambda^2\Gamma\left(1+\frac{2}{k}\right)-\mu_T^2$$

- **척도 모수 η의 영향**
  - ✓ $f_T(t;\beta,\eta)=\frac{\beta}{\eta^\beta}t^{\beta-1}e^{-(t/\eta)^\beta}$
  - ✓ η: 특성 수명 = 63.2% 고장
  - ✓ η = 40,000 hrs (Ball bearing)

형상모수 (β)	3		
척도모수 (η)	500	1,000	1,500







(a) PDF (b) CDF

Figure 5.3: Weibull Distribution

The Weibull is a very flexible life distribution model with two parameters.

- When k = 1, the Weibull reduces to the exponential model with $\mu_T = 1/\lambda$.
- For k < 1, failure rates are typical of infant mortality and decrease.
- For k > 1, failure rates are typical of aging effects and increase.
- For k = 2, the Weibull becomes the Rayleigh distribution.
- For k > 4, the Weibull becomes closer to a normal.

5.2.3 Normal Distribution

PDF:

$$f_T(t;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\right\}$$

where μ and σ are the mean and standard deviation of the distribution.

CDF:

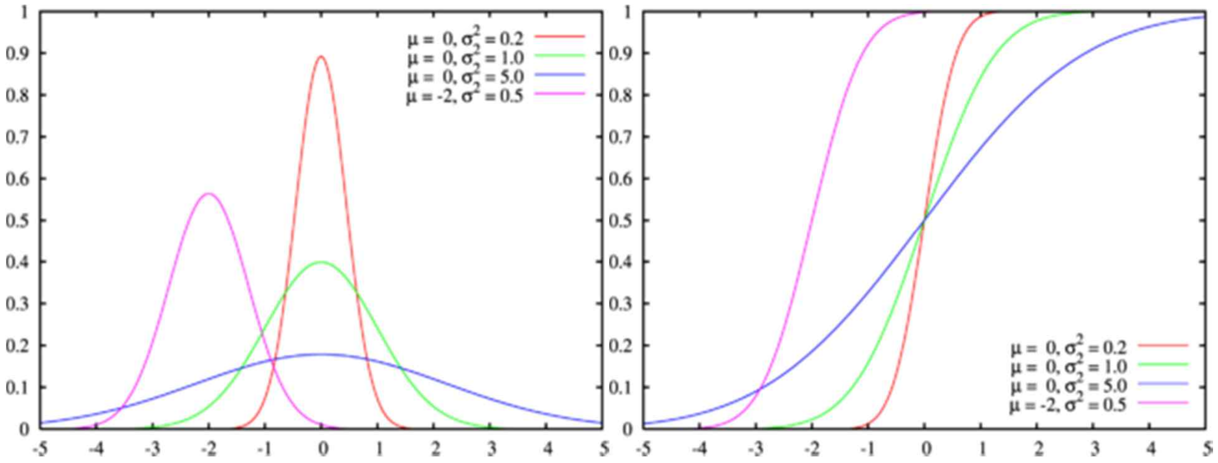
$$F_T(t;\lambda)=\int_{-\infty}^{t}\frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{\tau-\mu}{\sigma}\right)^2\right\}d\tau=\Phi\left(\frac{t-\mu}{\sigma}\right)$$

Reliability and Hazard Functions:

$$R(t)=1-\Phi\left(\frac{t-\mu}{\sigma}\right) \quad \text{and} \quad h(t)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\left(\frac{t-\mu}{\sigma}\right)^2\right\}\left\{1-\Phi\left(\frac{t-\mu}{\sigma}\right)\right\}^{-1}$$

MTTF:

$$\text{MTTF}=\mu_T=\mu \quad \text{and} \quad \sigma_T^2=\sigma^2$$



(a) PDF (b) CDF

Figure 5.4: Normal Distribution

The normal distribution describes the life of a tread on a tire or the cutting edge on a machine tool where the wearout time (μ) is reasonably well-defined.

5.2.4 Other Distributions

Lognormal, Gamma, and others are available at http://www.itl.nist.gov/div898/handbook/apr/section1/apr16.htm.

Homework 17: *Reliability Function*

Suppose it is desired to estimate the failure rate of an electronic component. A test can be performed to estimate its failure rate. A target life is set to 2000 minutes. $R(t) = P(T > 2000 \text{ minutes})$ Answer the following questions:

(1) Construct a histogram of TTF.

(2) Find out the best probability distribution model and its parameters, $f_T(t)$, for the TTF data.

(3) Construct a reliability function.

(4) Determine MTTF, standard deviation of TTF, and hazard function.

(5) Compare the reliability, n_f/N, from the TTF data with the reliability from the reliability function when $t = 2000$ where n_f is the number of failed components and N (= 100) is the total components.

Table 5.1: Data for 100 Electronics Time-To-Failure (TTF) [minute]

1703.2	1071.4	2225.8	1826.5	1131	2068.9	1573.5	1522.1	1490.7	2226.6
1481.1	2065.1	1880.9	2290.9	1786.4	1867.2	1859.1	1907.5	1791.8	1871
1990.4	2024.1	1688.6	1962.7	2191.7	1841	1814.1	1918.1	2237.5	1396.8
1692.8	707.2	2101.3	2165.4	1975.2	1961.6	2116.7	1373	1798.8	2248.4

1872.3	1597.8	1865.1	742.8	1436.7	1380.8	2258.2	1960	2182.8	1772.7
2003.6	1589.4	1988.3	1874.9	1859	2051.9	1763	1854.6	1974.7	2289.9
1945.7	1774.8	1579.6	1430.5	1855	1757.9	1029.3	1707.2	1864.7	1964.8
1719.4	1565.2	1736.8	1759.4	1939.4	2065.7	2258.5	2292.8	1452.5	1692.2
2120.7	1934.8	999.4	1919.9	2162.4	2094.9	2158.2	1884.2	1748.7	2260.3
1040.8	1535	1283.4	2267.7	2100.3	2007.9	2499.8	1902.9	1599.6	1567.5

5.3 Time-Dependent Reliability Analysis: (Physical) Accelerated Tests

The product life test would require a long-time test (e.g., 10^4 ~ 10^5 hours) under normal stress condition. The questions then arise of how to collect information about the corresponding life distributions under normal use conditions and how to make a product design reliable. There are two closely related problems that are typical with reliability data:

- Censoring (when the observation period ends, not all units have failed - some are survivors): Censored Type I (observe r for a fixed time, T) and Type II (observe T for a fixed number of failures, r).
- Lack of Failures (even if there is too much censoring, say a large number of units under observation, the information in the data can be limited due to the lack of actual failures).

→ How to deal with ***suspension data*** and to ***design life testing***

These problems cause practical difficulty when planning reliability assessment tests and analyzing failure data. A common way of tackling this problem is an Accelerated Life Testing (ALT).

- Compressed-time testing

  Many products experience on-off operation cycles instead of continuous operation. Reliability tests are performed in which appliance doors are more frequently opened and closed, consumer electronics is more frequently turned on and off, or pumps or motors are more frequently started and stopped to reach a designed life. These are referred to as compressed-time tests. The tests are used more steadily or frequently than in normal use, but the loads and environmental stresses are maintained at the level expected in normal use.

  If the cycle is accelerated too much, however, the conditions of operation may change and thus artificially generate different failure mechanisms. In other words, compressed-time testing (e.g., door open/close) may introduce different failure mechanisms instead of a primary failure mechanism under normal field operation.

- Advanced stress testing (or physical acceleration testing)

  Failure mechanisms may not be accelerated using the forgoing time-compressed testing. Advanced stress testing, however, may be employed to accelerate failures, since as increased loads or harsher environments are applied to a device, an increased failure rate may be observed. If a decrease in reliability can be quantitatively related to an increase in stress level, the life tests can be performed at high stress levels, and the reliability at normal levels inferred. Both random failures and aging effects may be the subject of advanced stress tests.

  Some engineering instances include:
  - In the electronics industry, components are tested at elevated temperatures to increase the incidence of random failure.
  - In the nuclear industry, pressure vessel steels are exposed to extreme levels of neutron irradiation to increase the rate of failure.

5.3.1 Physical Acceleration (or True Acceleration)

Physical acceleration means that operating a unit at high stress (i.e., higher temperature or voltage or humidity or duty cycle, etc.) produces the same failures that would occur at normal-use stresses, except that they happen much quicker. Failure may be due to mechanical fatigue, corrosion, chemical reaction, diffusion, migration, etc. These are the same causes of failure under normal stress; the time scale is simply different.

Exercise: Non-parametric process
Accelerated life tests are run on four sets of 12 flashlight bulbs and the failure times in minutes are found in Table 5.2. Estimate the MTTF at each voltage and extrapolate the results to the normal operating voltage of 6.0 volts.

Table 5.2: Life Data for Flashlight Bulbs (TTF) [minute]

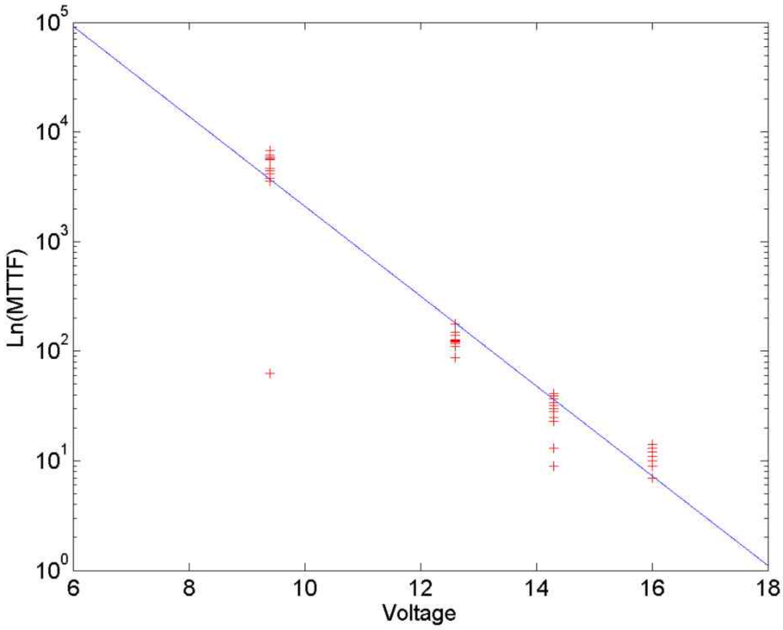
Voltage	9.4	12.6	14.3	16
1	63	87	9	7
2	3542	111	13	9
3	3782	117	23	9
4	4172	118	25	9
5	4412	121	28	9
6	4647	121	30	9

7	5610	124	32	10
8	5670	125	34	11
9	5902	128	37	12
10	6159	140	37	12
11	6202	148	39	13
12	6764	177	41	14

Solution:
The MTTFs can be obtained as

MTTF(9.4 voltage) = 4,744 mim.
MTTF(12.6 voltage) = 126 mim.
MTTF(14.3 voltage) = 29.0 mim.
MTTF(16.0 voltage) = 10.3 mim.

```
>> y = load TTF.dat
>> m(1)=log(mean(y(:,1)));m(2)=log(mean(y(:,2)));...
>> m(3)=log(mean(y(:,3)));m(4)=log(mean(y(:,4)));
>> p=polyfit(x,m,1)
p =
  -0.9438   17.0917
>> hold on; x=[6:0.01:18]; y=exp(p(1)*x+p(2)); plot(x,y)
```



In the figure above, MTTF versus voltage is plotted in a logarithmic scale:

The least-square fit indicates
$$\text{Ln(MTTF)} = -0.9438\times v + 17.0917$$

Hence,

MTTF = exp(17.0917 – 0.9438×v) = 241× 10^6 exp(–0.9438×v) [min]
= 1.8385×10^4 exp(–0.9438×v) days

At 6 volts:
MTTF = 1.8385×10^4 exp(–0.9438×6) days = 64 days = 2.13 months
= 9.184×10^4 minutes

The previous approach is a non-parametric process, while straightforward. It has several drawbacks relative to the parametric methods.

1. It requires that a complete set of life data be available at each stress level in order to use the sample mean to calculate the MTTF.
2. Without attempting to fit the data to a distribution, one has no indication whether the shape, as well as the time scale of the distribution, is changing. Since the changes in distribution shape are usually indications that a new failure mechanism is being activated by the higher-stress levels, there is a greater danger that the non-parametric estimate will be inappropriately extrapolated.

We use the following notation:

t_s = TTF at stress t_u = corresponding TTF at use
$F_s(t)$ = CDF at stress $F_u(t)$ = CDF at use

When there is a true acceleration, changing stress is equivalent to transforming the time scale used to record when failures occur. The transformations commonly used are *linear*, which means that TTF at high stress just has to be multiplied by a constant (the **acceleration factor**) to obtain the equivalent TTF at use.

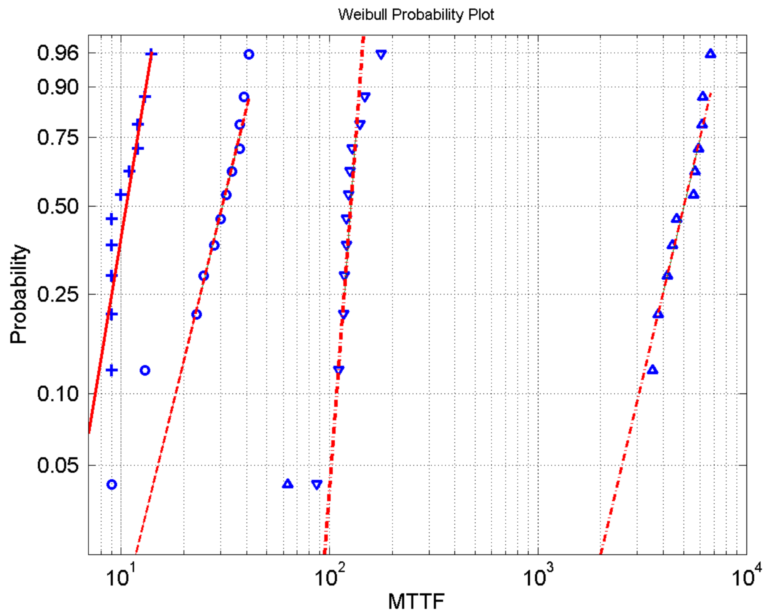
$$F_u(t_u) \rightarrow F_s(t_s) = F_s(t_s = t_u/AF)$$

The Weibull and lognormal distributions are particularly well suited for the analysis of advanced-stress tests, for in each case there is a scale parameter that is inversely proportional to the acceleration factor and a shape parameter that should be unaffected by acceleration.

Exercise: Parametric process
Let us consider the Weibull distribution as

$$F_T(t;\lambda) = 1 - \exp\left[-(t/\lambda)^k\right]$$

```
>> close
>> wblplot(y(:,1)),hold on; wblplot(y(:,2)); wblplot(y(:,3)); wblplot(y(:,4));
```




```
>> wblfit(y(:,1))
ans =
  1.0e+003 *
   5.0904    0.0022
```
→ first parameter for scale (λ) and second for shape (k)

```
>> wblfit(y(:,2))
ans =
  135.4589   5.9462
>> wblfit(y(:,3))
ans =
   32.2150    3.6187
>> wblfit(y(:,4))
ans =
   11.1620    5.6660
>> wblfit(y(2:12,1))
```
→ excluding one outlier

```
ans =
  1.0e+003 *
   5.5959   0.0058
```

Assume that the shape parameter (k: second value) be unchanged but the scale parameter (λ: first value) be changed.

We use the following notation:

$f_s(t)$ = PDF at stress $f_u(t)$ = PDF at use
$h_s(t)$ = failure rate at stress $h_u(t)$ = failure rate at use

Then, an acceleration factor AF between stress and use means the following relationships hold:

Linear Acceleration Relationships

MTTF	$t_u = AF \times t_s$
Failure Probability	$F_u(t_u) \rightarrow F_s(t_u/AF)$
Reliability	$R_u(t_u) \rightarrow R_s(t_u/AF)$
PDF	$f_u(t) \rightarrow (1/AF) \times f_s(t_u/AF)$
Failure Rate	$h_u(t) \rightarrow (1/AF) \times h_s(t_u/AF)$

5.3.2 Common Acceleration Models

- Arrehenius
  One of the earliest and most successful acceleration models predicts how TTF varies with temperature. This empirical model is known as the Arrhenius equation as

$$TTF = A\exp\left\{\frac{\Delta H}{k\theta}\right\} \quad \text{or} \quad TTF = A\exp\left\{\frac{B}{\theta}\right\} \tag{62}$$

with θ denoting temperature measured in degrees Kelvin (273.16 + degrees Celsius) at the point when the failure process takes place and k is Boltzmann's constant (8.617 x 10^{-5} in ev/K). The constant A is a scaling factor that drops out when calculating acceleration factors, with ΔH denoting the activation energy, which is the critical parameter in the model.
The acceleration factor between a high temperature θ_2 and a low temperature θ_1 is given by

$$AF = \frac{t_1}{t_2} = \exp\left\{\frac{\Delta H}{k}\left[\frac{1}{\theta_1} - \frac{1}{\theta_2}\right]\right\} \tag{63}$$

The value of ΔH depends on the failure mechanism and the materials involved, and typically ranges from 0.3 to 1.5, or even higher. Acceleration factors between two temperatures increase exponentially as ΔH increases.

Using the value of k given above, this can be written in terms of θ in degrees Celsius as

$$AF = \exp\left\{\Delta H \times 11605 \times \left[\frac{1}{(\theta_1 + 273.16)} - \frac{1}{(\theta_2 + 273.16)}\right]\right\} \tag{64}$$

Note that the only unknown parameter in this formula is ΔH.

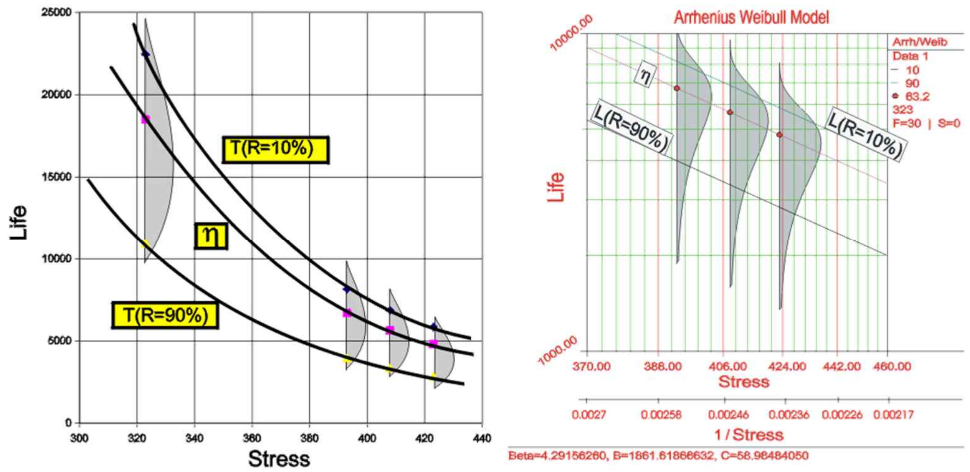
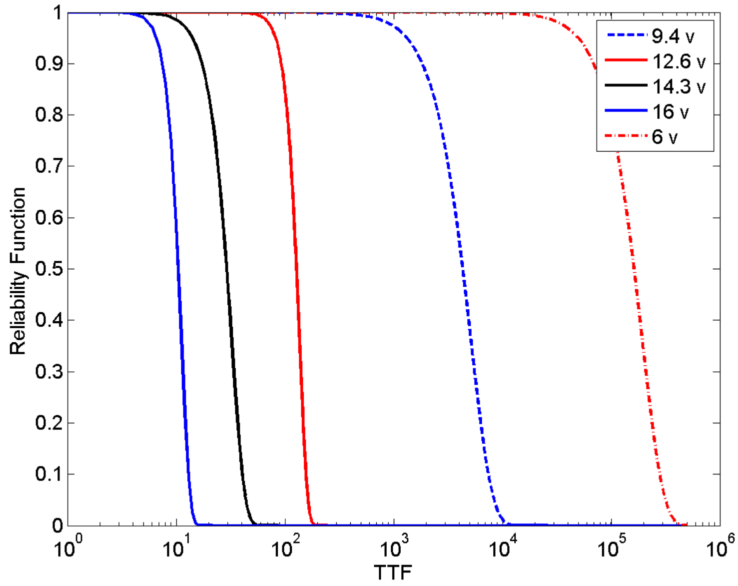


Figure 5.5 Arrehenius plot for Weibull life distribution
(http://www.weibull.com/AccelTestWeb/arrhenius_relationship_chap_.htm)

Exercise: Parametric process
Consider the accelerated life tests for the four sets of 12 flashlight bulbs and the failure times in minutes are found in the Table 4.2. Estimate the MTTF at normal operating 6.0 voltage using Arrehius model. Assume v1 = 9.4 and v2 = 12.6. Accordingly, t1 = 4744 and t2 = 126. Hence, AF =4744/126 = 37.65. Reliability function can be calculated as

```
>> t=[0:10:500000];r1=exp(-(t./5090.4).^2.2); plot(t,r1)
>> hold on;
>> t=[0:1:500000];r2=exp(-(t./135.5).^5.9); plot(t,r2)
>> t=[0:1:500000];r3=exp(-(t./32.22).^3.6); plot(t,r3)
>> t=[0:1:500000];r4=exp(-(t./11.16).^5.7); plot(t,r4)
>> t=[0:10:500000];r5=exp(-(t./5090.4/37.65).^2.2); plot(t,r5)
>> R = @(t) exp(-(t./5090.4/37.65).^2.2);
>> MTTF = quad(R,0,10^6)
 MTTF =
 1.6973e+005
>> R = @(t) exp(-(t./5595.9/37.65).^5.8);
>> MTTF = quad(R,0,10^6)
 MTTF =
 1.9509e+005
```



The Arrhenium model parameters can be also calculated.

The Arrhenius model has been used successfully for failure mechanisms that depend on chemical reactions, diffusion processes or migration processes. This covers many of the thermally-induced mechanical failure modes that cause electronic equipment failure.

- Eyring
  Henry Eyring's contributions to chemical reaction rate theory have led to a very general and powerful model for acceleration known as the Eyring Model. This model has several key features:

  ✓ It has a theoretical basis from chemistry and quantum mechanics.
  ✓ If a chemical process (chemical reaction, diffusion, corrosion, migration, etc.) is causing degradation leading to failure, the Eyring model describes how the rate of degradation varies with stress or, equivalently, how TTF varies with stress.
  ✓ The model includes temperature and can be expanded to include other relevant stresses.
  ✓ The temperature term by itself is very similar to the Arrhenius empirical model, explaining why that model has been so successful in establishing the connection between the ΔH parameter and the quantum theory concept of "activation energy needed to cross an energy barrier and initiate a reaction".

  The model for temperature and one additional stress takes the general form:

$$TTF = A\theta^{\alpha} \exp\left\{\frac{\Delta H}{k\theta} + \left(B + \frac{C}{\theta}\right)S_1\right\} \tag{65}$$

for which S_1 could be some function of voltage or current or any other relevant stress and the parameters k, ΔH, B, and C determine acceleration between stress combinations. As with the Arrhenius Model, k is Boltzmann's constant and temperature is in degrees Kelvin. If we want to add an additional non-thermal stress term, the model becomes

$$t_f = A\theta^{\alpha} \exp\left\{\frac{\Delta H}{k\theta} + \left(B_1 + \frac{C_1}{\theta}\right)S_1 + \left(B_2 + \frac{C_2}{\theta}\right)S_2\right\} \tag{66}$$

and as many stresses as are relevant can be included by adding similar terms.

Advantages of the Eyring Model
- ✓ Can handle many stresses.
- ✓ Can be used to model degradation data as well as failure data.
- ✓ The ΔH parameter has a physical meaning and has been studied and estimated for many well known failure mechanisms and materials.

Disadvantages of the Eyring Model
- ✓ Even with just two stresses, there are 5 parameters to estimate. Each additional stress adds 2 more unknown parameters.
- ✓ Many of the parameters may have only a second-order effect. For example, setting $\alpha = 0$ works quite well since the temperature term then becomes the same as in the Arrhenius model. Also, the constants C_1 and C_2 are only needed if there is a significant temperature interaction effect with respect to the other stresses.

- Other models
  a. (Inverse) Power Rule for Voltage
  b. Exponential Voltage Model
  c. Two Temperature/Voltage Models
  d. Electromigration Model
  e. Three-Stress Models (Temperature, Voltage, and Humidity)
  f. Coffin-Manson Mechanical Crack Growth Model

  Refer to http://www.itl.nist.gov/div898/handbook/apr/section1/apr153.htm

Homework 18: *Failure analysis of a paper clip twisting*
Answer the following questions:
(a) Identify data outlier(s) and justify it.
(b) Develop a probability density function model for TTF data under twisting moment. Use a Weibull distribution.
(c) Calculate the MTTF and develop reliability function and failure rate models for the TTF data under a twisting condition.

Homework 19: *Life analysis of a paper clip bending*
Answer the following questions:
(a) Develop probability density function models for TTF data under four bending conditions, 180^o, 135^o, 90^o, and 45^o. Use a Weibull distribution and report the statistical parameters in table.
(b) Discuss the result above.
(c) Use the Arrehenius model with the TTF data (180^o, 135^o, 90^o) to calculate the Accelerating Factor (AF) and plot Log(Life) vs Stress(bending angle).
(d) Predict a TTF under a bending angle (45^o) using the Arrehenius model obtained in (c) and compare the predicted TTF with the observed TTF from (a).

5.4 Degradation-based Simulations

5.4.1 Fatigue
See the handout, fatigue_wiki.pdf

5.4.2 Wear
See the handout, wear_wiki.pdf

5.4.3 Corrosion
See the handout, corrosion_wiki.pdf

5.4.4 Creep
See the handout, creep_wiki.pdf

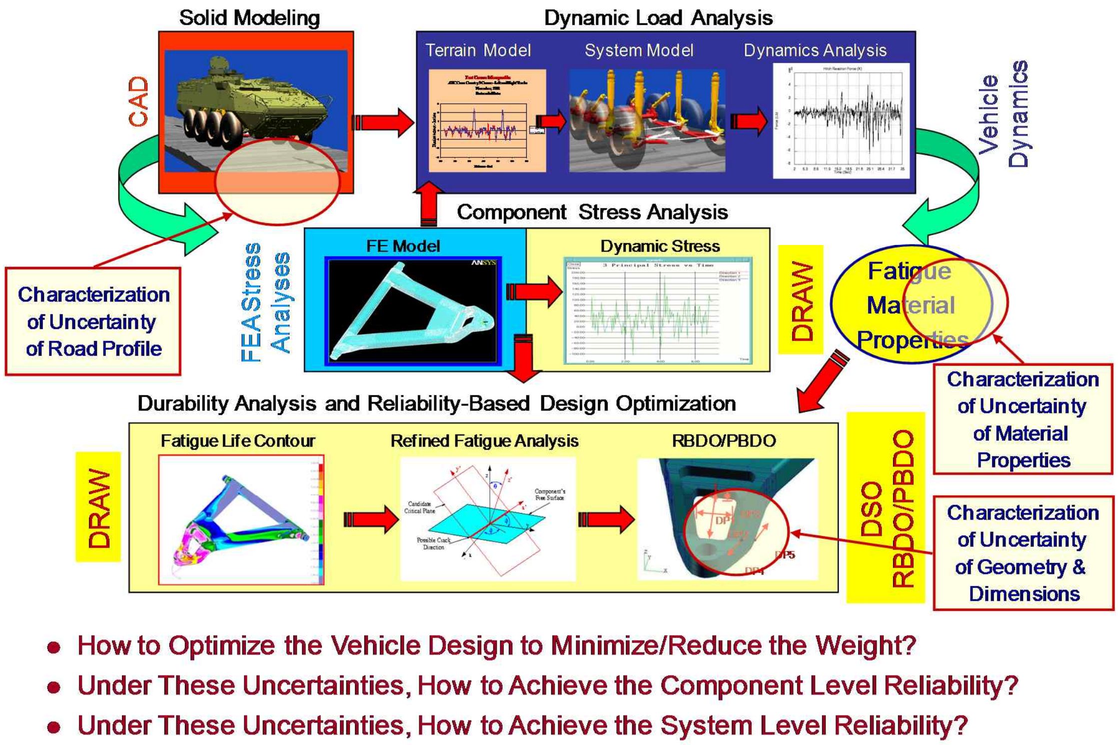


Figure 5.6: Fatigue Simulation Model – Fatigue Life = Y(**X**)

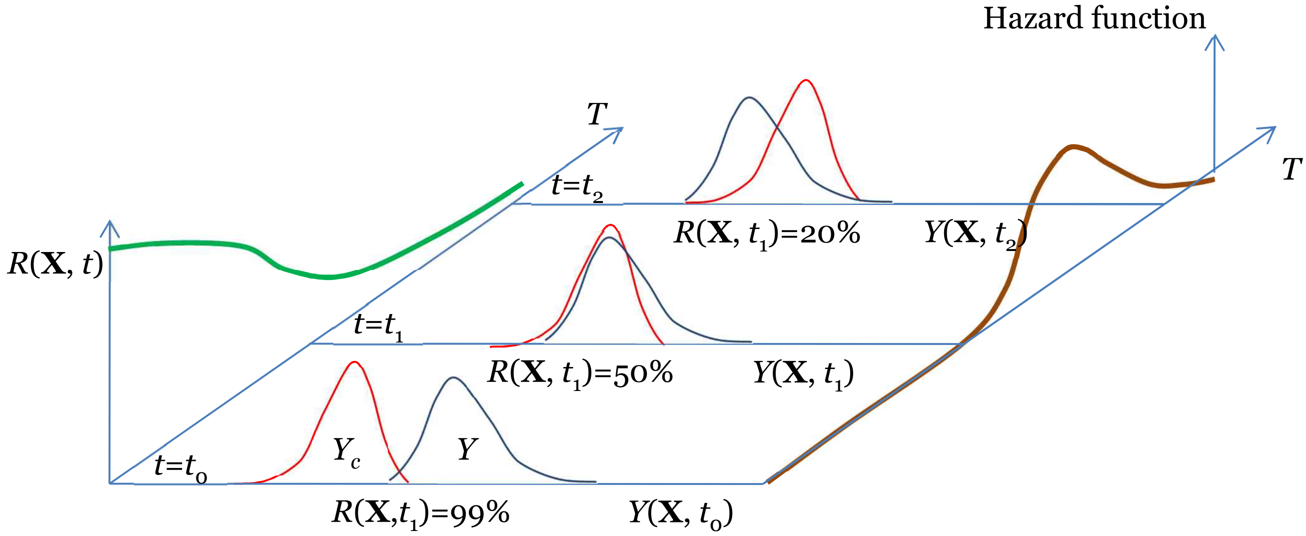


Figure 5.7: General Description of Reliability (L-Type)

5.5 Health monitoring and prognostics

Accelerated life testing (ALT) is capable of providing an instantaneous reliability estimate for an engineered system based on degradation characteristics of historical units. We refer to this approach as the classical reliability approach, which incorporates population characteristics into reliability estimation by modeling a life distribution. However, this classical reliability approach only provides an overall reliability estimate that takes the same value for the whole population of units. In engineering practice, we are more interested in investigating the specific reliability information of a particular unit under its actual life cycle conditions to determine the advent of a failure and mitigate potential risk.

To overcome the limitation of the classical reliability approach, prognostics and health management (PHM) has recently emerged as a key technology to evaluate the current health condition (health monitoring) and predict the future degradation behavior (health prognostics) of an engineered system throughout its lifecycle. In general, PHM consists of four basic functions: health sensing function, health reasoning function, health prognostics function and health management functions (see Fig. 5.8 for he first three functions).

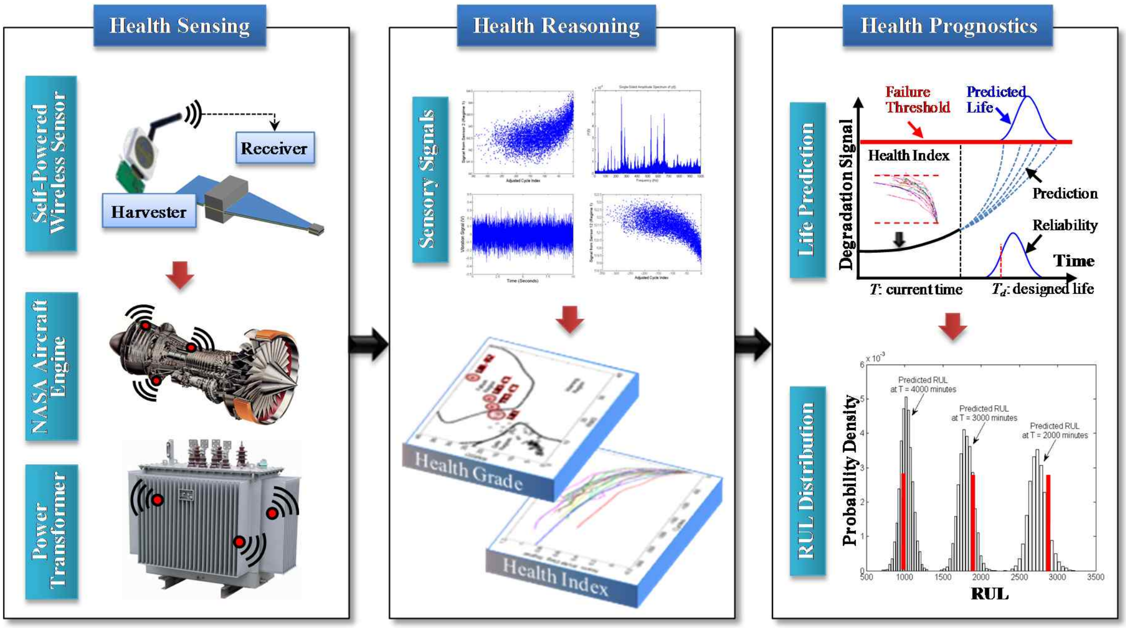


Figure 5.8: Basic PHM Functions

- Health Sensing Function: To acquire sensory signal with in-situ monitoring techniques and to ensure high damage detectability by designing an optimal wireless sensor network (WSN);
- Health Reasoning Function: To extract system health relevant information in real-time with feature extraction techniques and to classify system health condition with health classification techniques;
- Health Prognostics Function: To predict the time remaining before an engineered system no longer performs the required function(s) or the remaining useful life (RUL) in real-time with advanced machine learning techniques;

- Health Management Function: To enable optimal decision making on maintenance of engineered systems based on RUL predictions from health prognostics function with trade-off analysis and random process modeling techniques.

In recent years, prognostics and health management (PHM) has been successfully applied to many engineered systems to assess their health conditions in real-time under actual operation conditions and adaptively enhance life cycle reliabilities with condition-based maintenance that will effectively avoid unexpected failures. Figure 5.8 exemplifies several engineered systems that capitalize on PHM to enable an early anticipation of failure, to develop cost-effective maintenance strategies and to seek opportunities for life extensions.

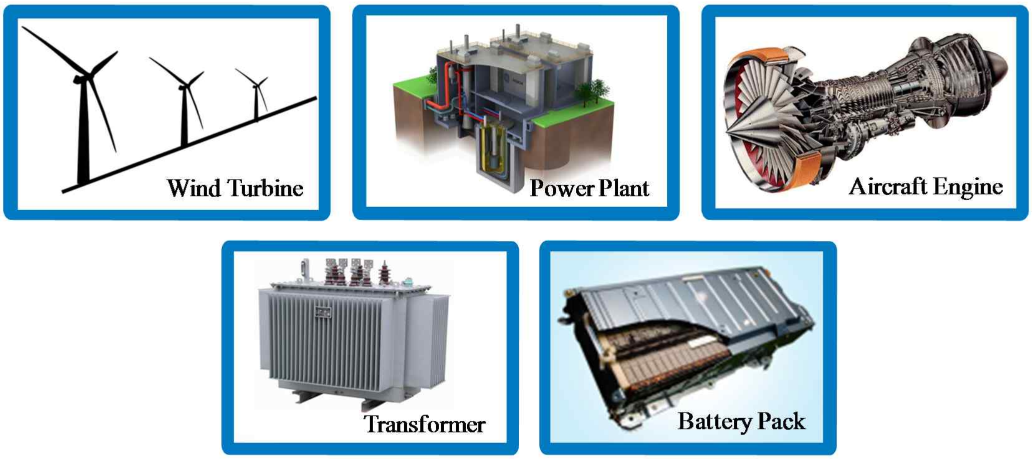


Figure 5.9: Engineered Systems Capitalizing on PHM

An example is provided in Fig. 5.10 to demonstrate the three main PHM functions.

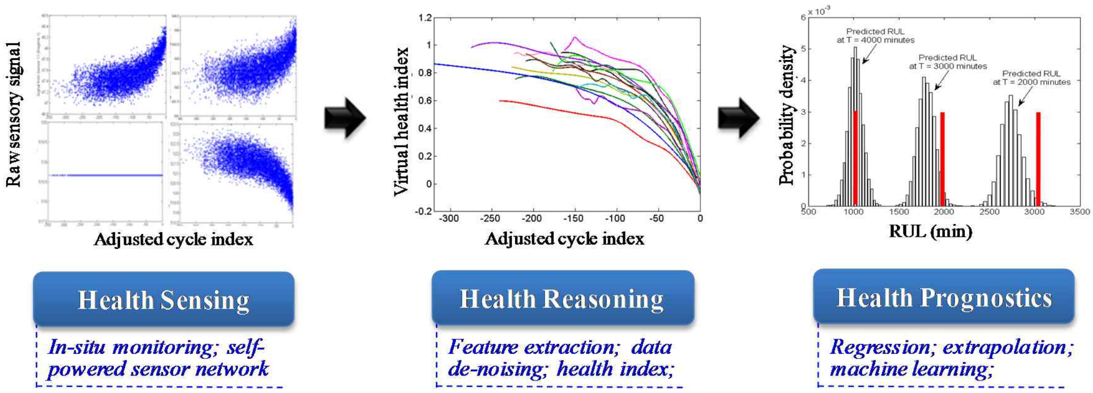


Figure 5.10: An Example Illustrating Three Main PHM Functions.