

# TMA4275 LIFETIME ANALYSIS

## Slides 2: General concepts for lifetime modeling

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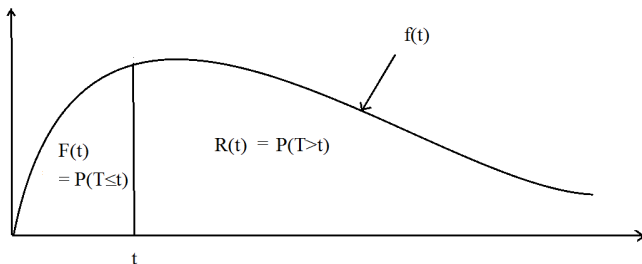
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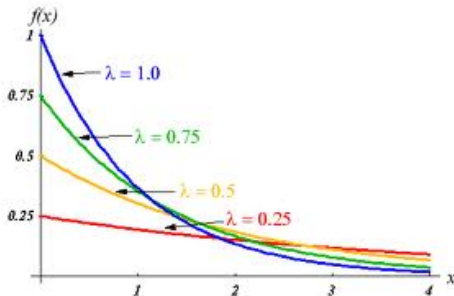
*NTNU, Spring 2014*

The lifetime  $T$  of an individual or unit is a *positive* and *continuously distributed* random variable.

- The probability density function (pdf) is usually called  $f(t)$ ,
- the cumulative distribution function (cdf)  $F(t)$  is then given by  $F(t) = P(T \leq t) = \int_0^t f(u)du$ ,
- the reliability (or: survival) function is defined as  $R(t) = P(T > t) = 1 - F(t) = \int_t^\infty f(u)du$ .



# EXAMPLE: EXPONENTIAL DISTRIBUTION

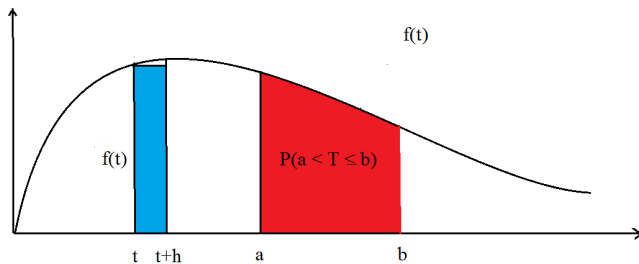


$$f(t) = \lambda e^{-\lambda t}$$

$$F(t) = 1 - e^{-\lambda t}$$

$$R(t) = e^{-\lambda t}$$

# INTERPRETATION OF DENSITY FUNCTION



$$f(t) = F'(t)$$

$$P(a < T \leq b) = \int_a^b f(u) du = F(b) - F(a)$$

$$P(t < T \leq t+h) = \int_t^{t+h} f(u) du \approx f(t) \cdot h$$

Hence,

$$f(t) \approx \frac{P(t < T \leq t+h)}{h}$$

Suppose we know that unit is alive (functioning) at time  $t$ , i.e.  $T > t$ .

Then it is of interest to consider

$$P(t < T \leq t + h | T > t) = \frac{P(t < T \leq t + h)}{P(T > t)} \approx \frac{f(t)h}{R(t)}$$

(Recall *conditional probability*:  $P(A|B) = P(A \cap B)/P(B)$ ).

From this we define the *hazard function* (also called *hazard rate* or *failure rate*) of  $T$  at time  $t$  by:

$$z(t) = \lim_{h \rightarrow 0} \frac{P(t < T \leq t + h | T > t)}{h} = \frac{f(t)}{R(t)}$$

*Example:* For the exponential distribution we have

$f(t) = \lambda e^{-\lambda t}$  and  $R(t) = e^{-\lambda t}$ , so

$$z(t) = \frac{f(t)}{R(t)} = \lambda \text{ (not depending on time!).}$$

Since  $F(t) = 1 - R(t)$  we get,  $f(t) = F'(t) = -R'(t)$ , and hence

$$z(t) = \frac{f(t)}{R(t)} = -\frac{R'(t)}{R(t)}$$

Thus we can write,

$$\begin{aligned} \frac{d}{dt}(\ln R(t)) &= -z(t) \\ \Rightarrow \ln R(t) &= -\int_0^t z(u)du + c \\ \Rightarrow R(t) &= e^{-\int_0^t z(u)du + c} \end{aligned}$$

Since  $R(0) = 1$ , we have  $c = 0$ , so

$$R(t) = e^{-\int_0^t z(u)du} \equiv e^{-Z(t)}$$

where  $Z(t) = \int_0^t z(u)du$  is called the *cumulative hazard function*.

Recall from last slide:

- $Z(t) = \int_0^t z(u)du$
- $z(t) = Z'(t)$
- $R(t) = e^{-Z(t)}$

Since  $f(t) = F'(t) = -R'(t)$ , it follows that

$$f(t) = z(t)e^{-\int_0^t z(u)du} = z(t)e^{-Z(t)} \quad (1)$$

For exponential distribution:

$$Z(t) = \int_0^t \lambda du = \lambda t$$

so (1) gives (the well known formula)

$$f(t) = \lambda e^{-\lambda t}$$

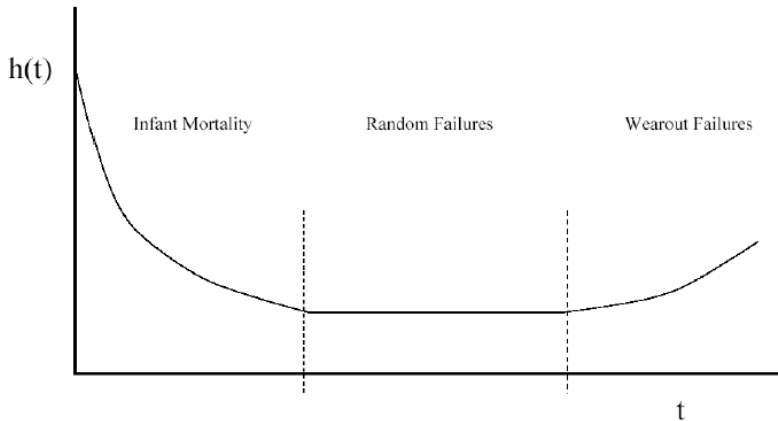
# OVERVIEW OF FUNCTIONS DESCRIBING DISTRIBUTION OF LIFETIME $T$

Function	Formula	Exponential distr
Density (pdf)	$f(t)$	$= \lambda e^{-\lambda t}$
Cum. distr. (cdf)	$F(t)$	$= 1 - e^{-\lambda t}$
Rel/surv function	$R(t) = 1 - F(t)$	$= e^{-\lambda t}$
Hazard function	$z(t) = f(t)/R(t)$	$= \lambda$
Cum hazard function	$Z(t) = \int_0^t z(u)du$	$= \lambda t$
	$R(t) = e^{-Z(t)}$	$= e^{-\lambda t}$
	$f(t) = z(t)e^{-Z(t)}$	$= \lambda e^{-\lambda t}$



- 1 Suppose the reliability function of  $T$  is  $R(t) = e^{-t^{1.7}}$ . Find the functions  $F(t)$ ,  $f(t)$ ,  $z(t)$ ,  $Z(t)$ .
- 2 Show that if you get to know only one of the functions  $R(t)$ ,  $F(t)$ ,  $f(t)$ ,  $z(t)$ ,  $Z(t)$ , then you can still compute all the other!

## Bathtub Curve Hazard Function



## MORE ON THE HAZARD FUNCTION

Recall that  $z(t) = \lim_{h \rightarrow 0} \frac{P(t < T \leq t+h | T > t)}{h}$ .

Thus

$$z(t)h \approx P(t < T \leq t+h | T > t) = P(\text{fail in } (t, t+h) | \text{alive at } t)$$

Suppose a typical  $T$  is large compared to time unit. Then for  $h = 1$ :

$$z(t) \approx P(t < T \leq t+1 | T > t) = P(\text{fail in next time unit} | \text{alive at } t)$$

Thus: Suppose we have  $n$  units of age  $t$ . How many can we expect to fail in next time unit?

$$e = n \cdot z(t)$$

In practice: Ask an expert: "If you have 100 components (of specific type) of age 1000 hours. How many do you expect to fail in the next hour"?

Answer is, say, "2". Looking at  $e = n \cdot z(t)$  we estimate;

$$\hat{z}(1000) = \frac{2}{100} = 0.02$$

Let  $T$  be the lifetime of a Norwegian measured in years.

Let  $z_M(t)$  be the hazard function for a male person as a function of the age  $t$ , while  $z_F(t)$  is the corresponding function for a female.

Look at the Mortality tables of Slides 1 and estimate  $z_M(21)$  and  $z_F(21)$ . Compare them and comment.

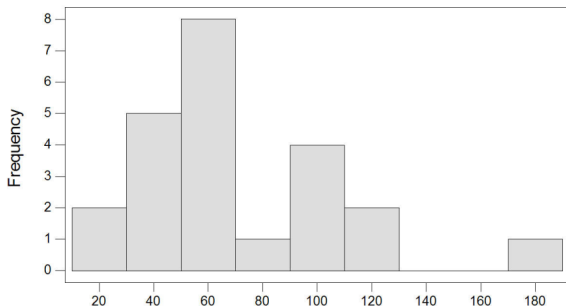
Do the same at age 72 years.

# RECALL BALL BEARING FAILURE DATA

17,88	28,92	33,00	41,52	42,12	45,60	48,40	51,84
51,96	54,12	55,56	67,80	68,64	68,64	68,88	84,12
93,12	98,64	105,12	105,84	127,92	128,04	173,40	

**Question:** *How can we fit a parametric lifetime model to these data?*

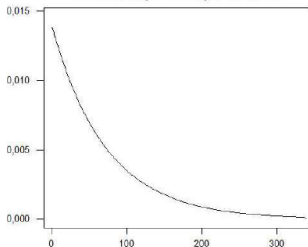
Histogram of Revolutions



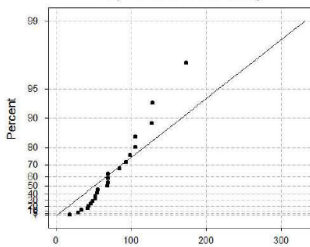
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



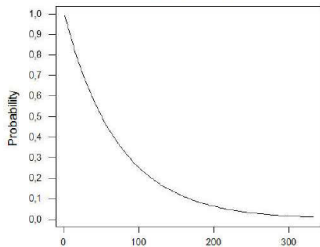
Exponential Probability



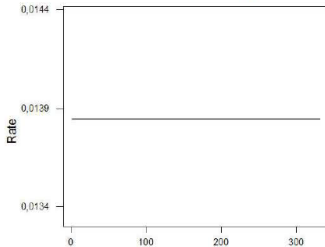
Shape 1  
 Scale 72,22  
 MTTF 72,22  
 Failure 23  
 Censor 0

Goodness of Fit  
 AD\* 3,341

Survival Function



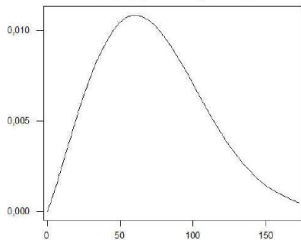
Hazard Function



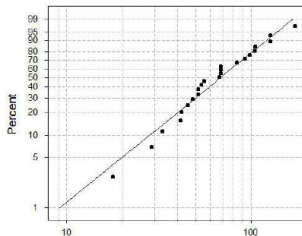
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



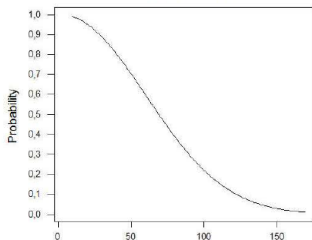
Weibull Probability



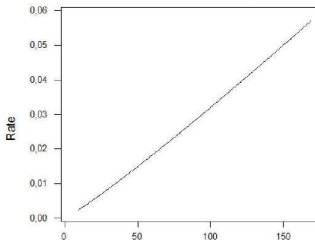
Shape 2,1018  
 Scale 81,675  
 MTTF 72,515  
 Failure 23  
 Censor 0

Goodness of Fit  
 AD\* 0,802

Survival Function



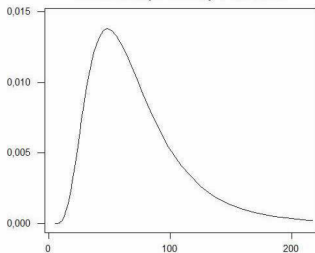
Hazard Function



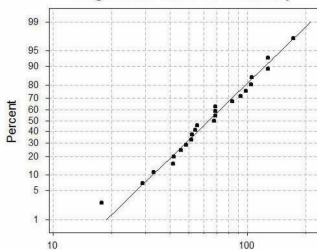
## Ball Bearings Failure Data

ML Estimates - Complete Data

Probability Density Function



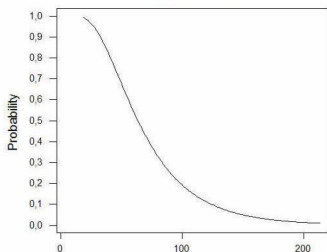
Lognormal base e Probability



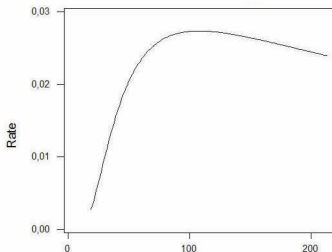
Location	4,1504
Scale	0,5217
MTTF	72,709
Failure	23
Censor	0

Goodness of Fit	
AD*	0,647

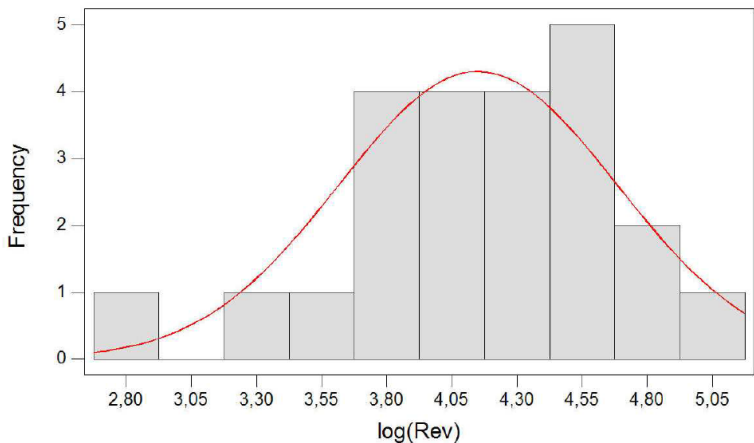
Survival Function



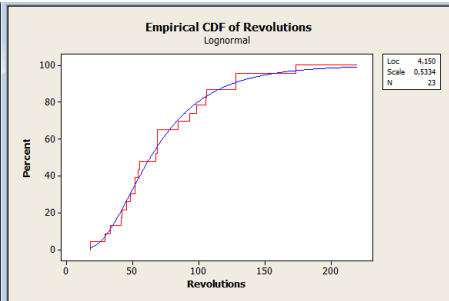
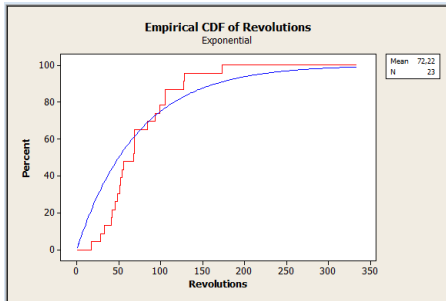
Hazard Function





Histogram of  $\log(\text{Rev})$ , with Normal Curve

# BB-DATA: EMPIRICAL DISTRIBUTION COMPARED TO PARAMETRIC FITS



- Simplest distribution used in the analysis of reliability data.
- Has the important characteristic that its hazard function is constant (does not depend on time  $t$ ).
- Popular distribution for some kinds of electronic components (e.g., capacitors or robust, high-quality integrated circuits).
- Might be useful to describe failure times for components that exhibit physical wearout only after expected technological life of the system, in which the component would be replaced.

- The theory of extreme values shows that the Weibull distribution can be used to model the minimum of a large number of independent positive random variables from a certain class of distributions.
  - Failure of the weakest link in a chain with many links with failure mechanisms (e.g. fatigue) in each link acting approximately independently.
  - Failure of a system with a large number of components in series and with approximately independent failure mechanisms in each component.
- The more common justification for its use is empirical: the Weibull distribution can be used to model failure-time data with a decreasing or an increasing hazard function.

- The lognormal distribution is a common model for failure times.
- It can be justified for a random variable that arises from the product of a number of identically distributed independent positive random quantities (remember central limit theorem for sum of normals).
- It has been suggested as an appropriate model for failure time caused by a degradation process with combinations of random rates that combine multiplicatively.
- Widely used to describe time to fracture from fatigue crack growth in metals.