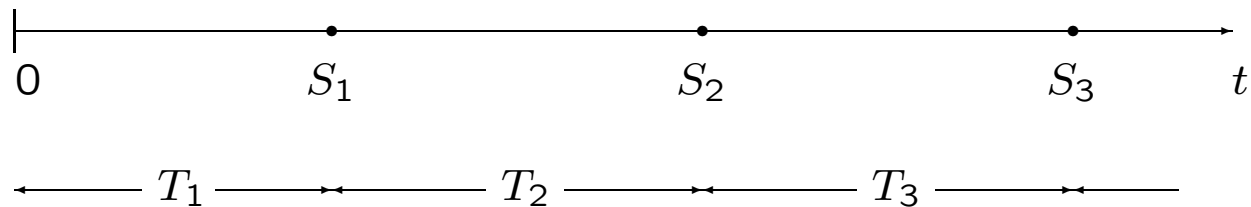


## REPAIRABLE SYSTEMS/RECURRENT EVENTS/COUNTING PROCESSES

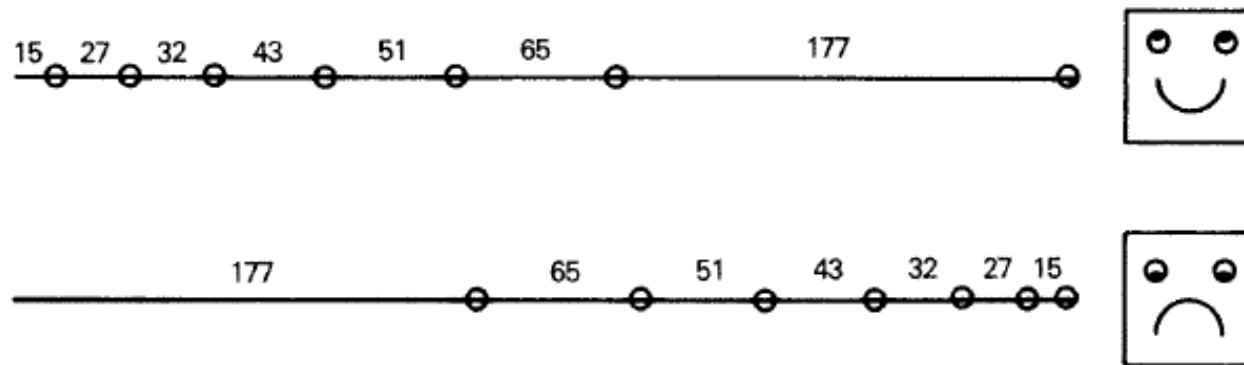
*Definition of repairable system (Ascher and Feingold 1984):*

“A repairable system is a system which, after failing to perform one or more of its functions satisfactorily, can be restored to fully satisfactory performance by any method, other than replacement of the entire system” .



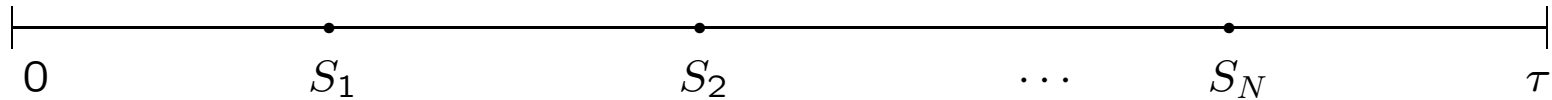
## “HAPPY” AND “SAD” SYSTEMS

Ascher and Feingold presented the following example of a “happy” and “sad” system:



- *Their claim:* Reliability engineers do not recognize the difference between these cases since they always treat times between failures as i.i.d. and fit probability models like Weibull.
- *Their conclusion:* Use point process models to analyze repairable systems data!

Today: Recurrent events extensively studied



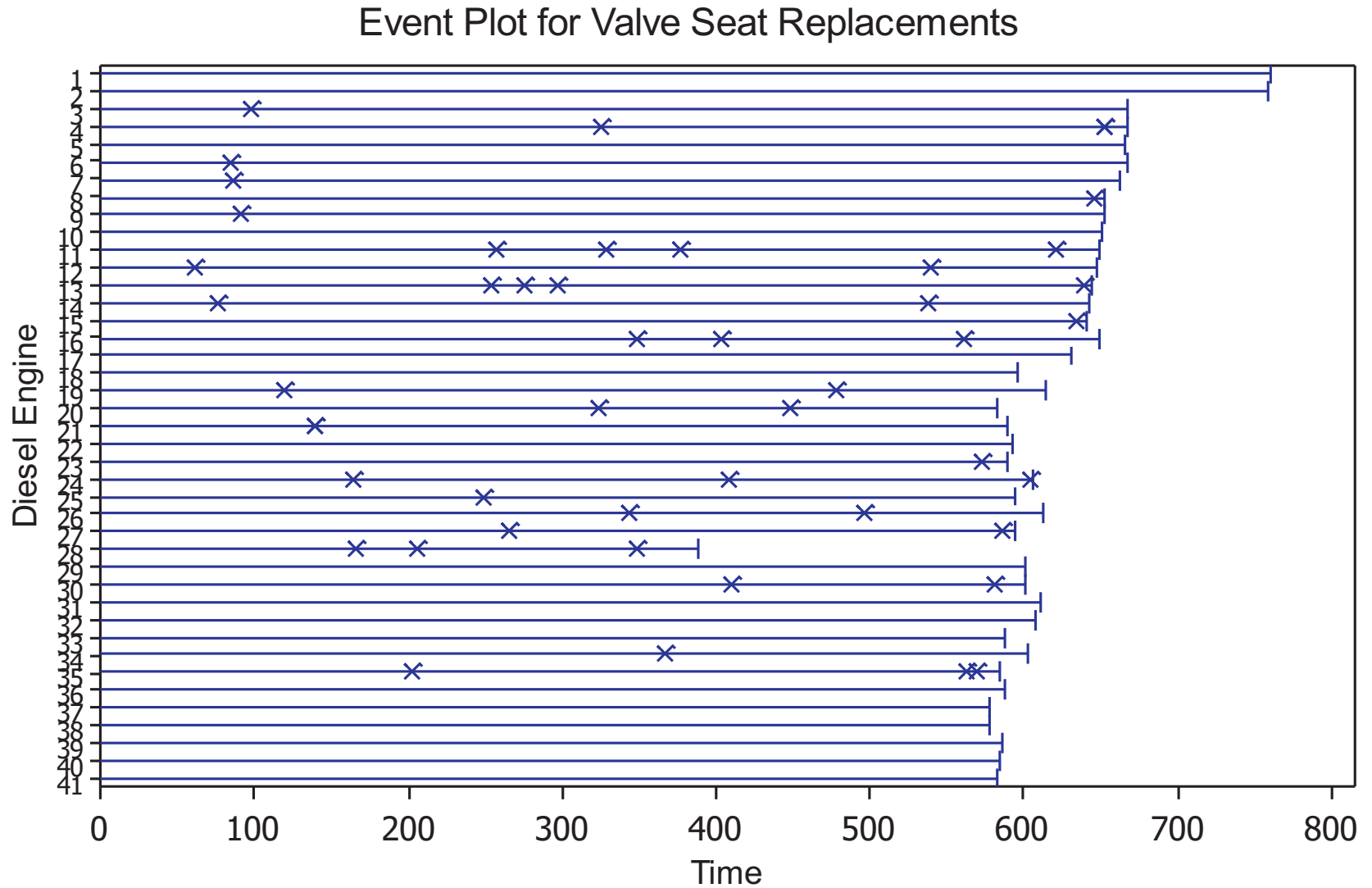
- Applications: engineering and reliability studies, public health, clinical trials, politics, finance, insurance, sociology, etc.

Reliability applications:

- breakdown or failure of a mechanical or electronic system
- discovery of a bug in an operating system software
- the occurrence of a crack in concrete structures
- the breakdown of a fiber in fibrous composites
- Warranty claims of manufactured products

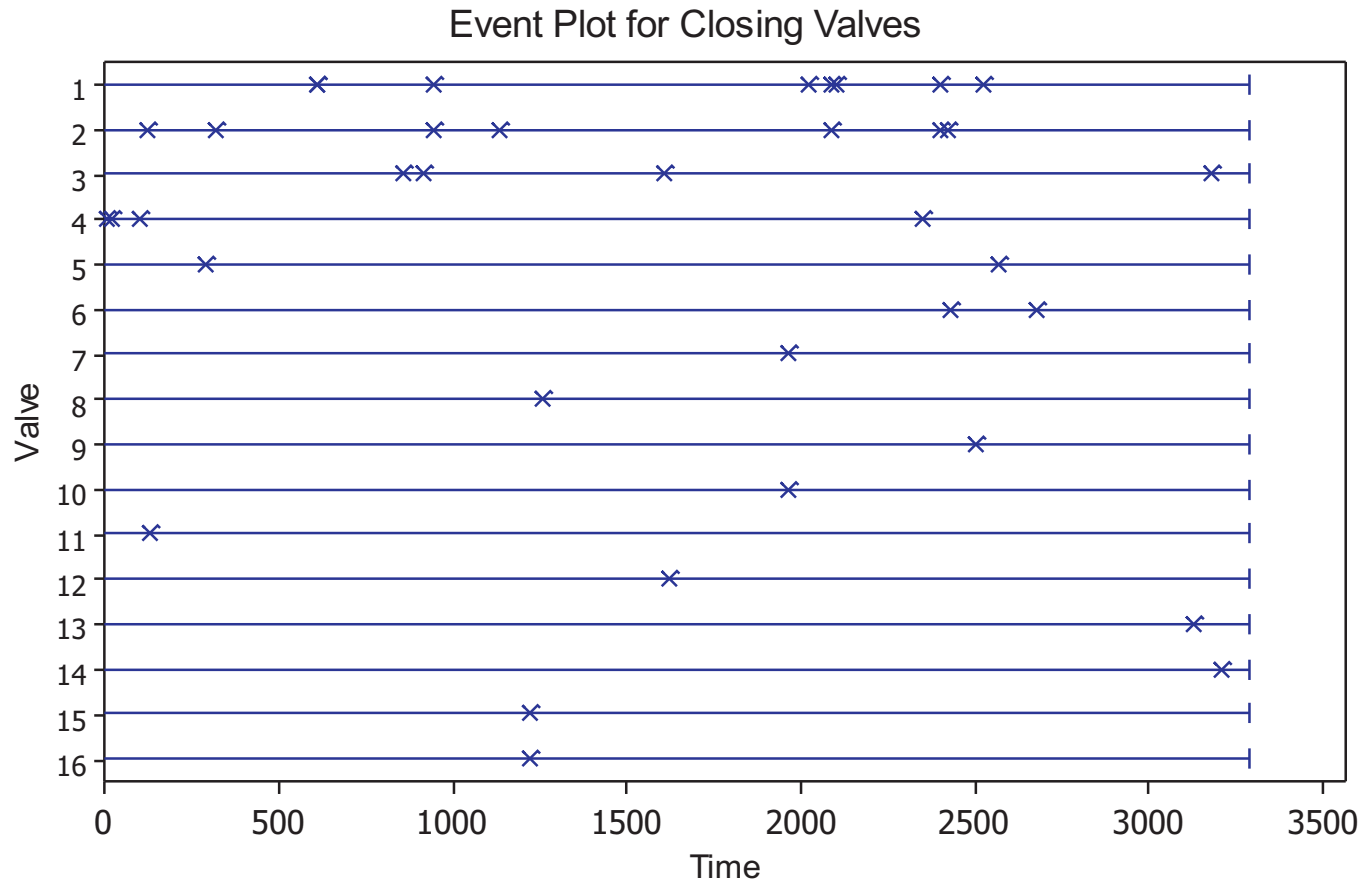
Nelson (1995): Valve seat data

- Times of valve-seat replacements in a fleet of 41 diesel engines



Bhattacharjee et al. (2003): Nuclear plant failure data

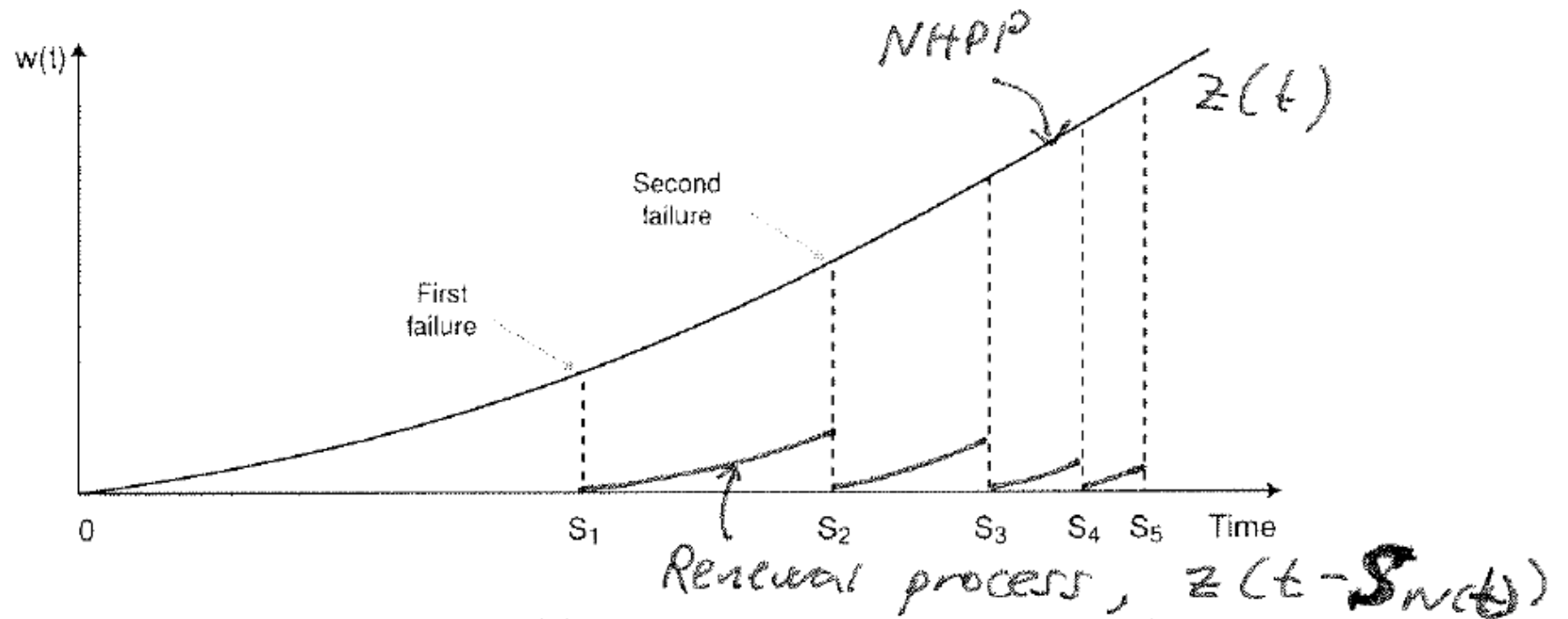
- Failure data for closing valves in safety systems at two nuclear reactor plants in Finland. Failures type: *External Leakage*, follow-up 9 years for 104 valves. 88 valves had no failures



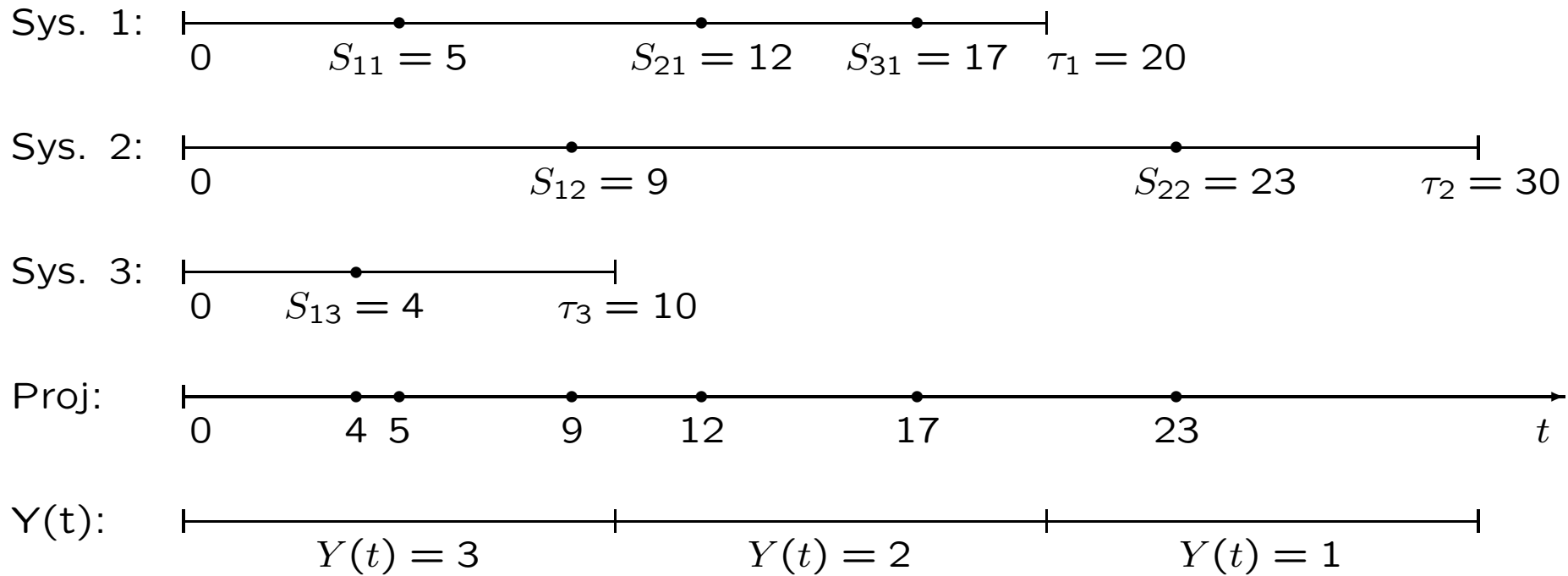
Aalen and Husebye (1991): Migratory motor complex (MMC) periods in 19 patients, 1-9 events per individual.

Individual	Observed periods (minutes)					
1	112 33	145 51	39 (54)	52	21	34
2	206	147	(30)			
3	284	59	186	(4)		
4	94	98	84	(87)		
5	67	(131)				
6	124 58	34 142	87 75	75 (23)	43	38
7	116	71	83	68	125	(111)
8	111	59	47	95	(110)	
9	98	161	154	55	(44)	
10	166	56	(122)			
11	63	90	63	103	51	(85)
12	47	86	68	144	(72)	
⋮			⋮			

# CONDITIONAL ROCOF BY MINIMAL REPAIR (NHPP) AND PERFECT REPAIR (RENEWAL PROCESS)



## SIMPLE EXAMPLE WITH THREE SYSTEMS

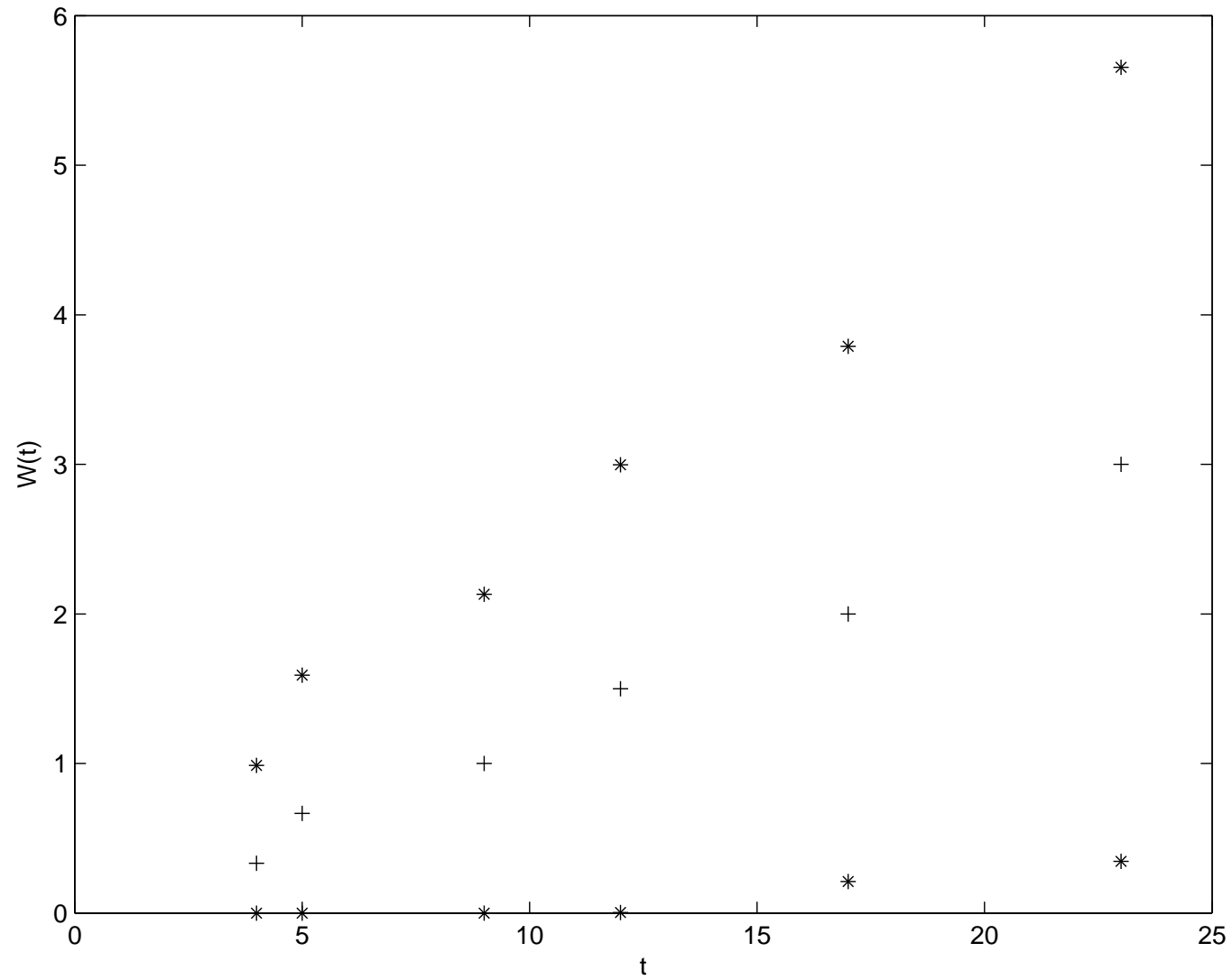




COMPUTATIONS FOR THE NELSON-AALEN ESTIMATOR

$t$	$1/Y(t)$	$1/Y(t)^2$	$\widehat{W}(t)$	$Var\widehat{W}(t)$	$SD\widehat{W}(t)$
4	1/3	1/9	1/3	1/9	0.3333
5	1/3	1/9	2/3	2/9	0.4714
9	1/3	1/9	1	1/3	0.5774
12	1/2	1/4	3/2	7/12	0.7638
17	1/2	1/4	2	5/6	0.9129
23	1	1	3	11/6	1.3540

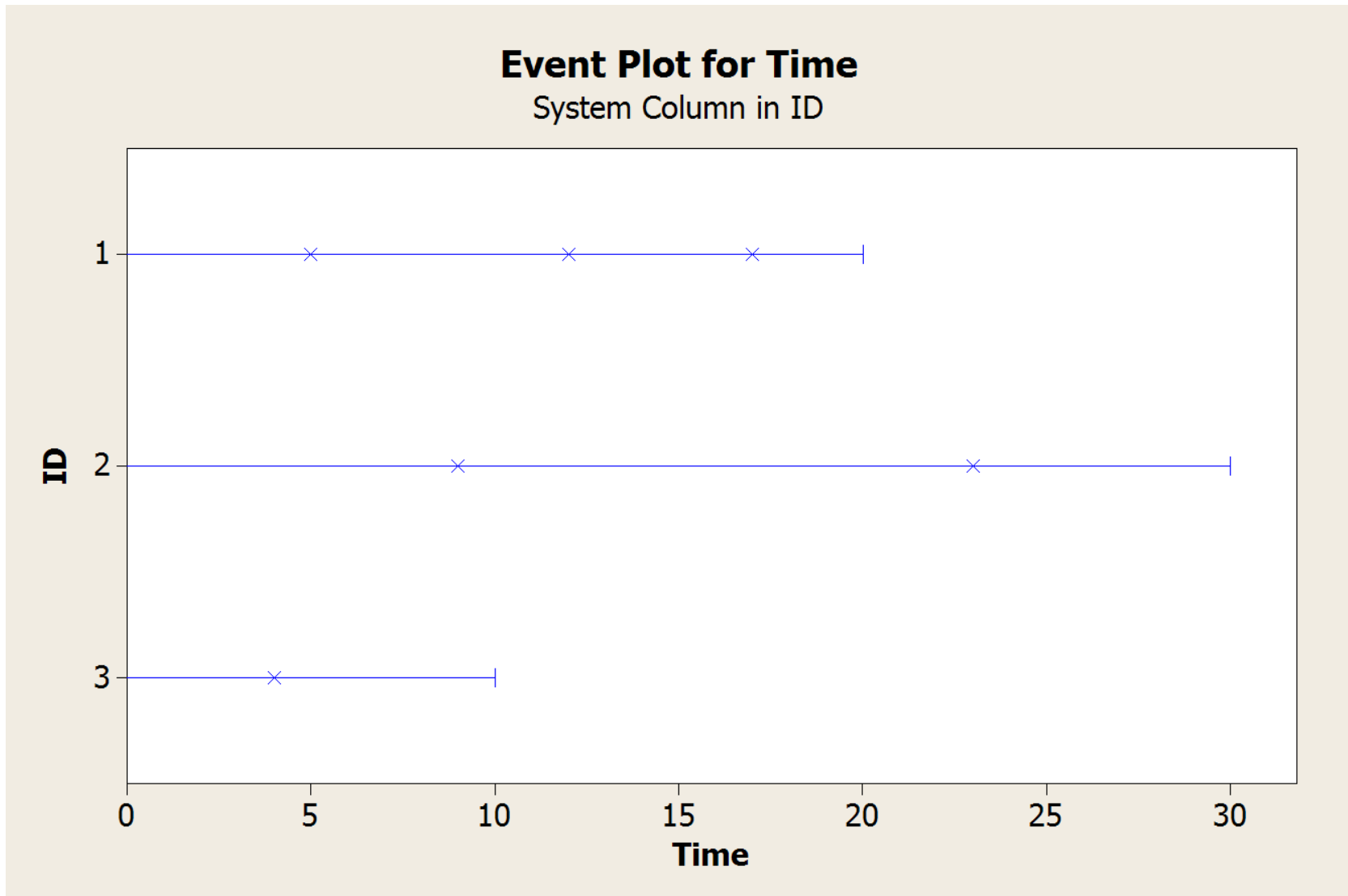
ESTIMATED  $W(t)$  with 95% confidence limits (Nelson-Aalen)



## Simple Example With 3 Systems

SimpleNHPP.MTW ***			
↓	C1	C2	C3
	ID	Time	
1	1	5	
2	1	12	
3	1	17	
4	1	20	
5	2	9	
6	2	23	
7	2	30	
8	3	4	
9	3	10	
10			

## Simple Example With 3 Systems



## Simple Example With 3 Systems

Results for: SimpleNHPP.MTW

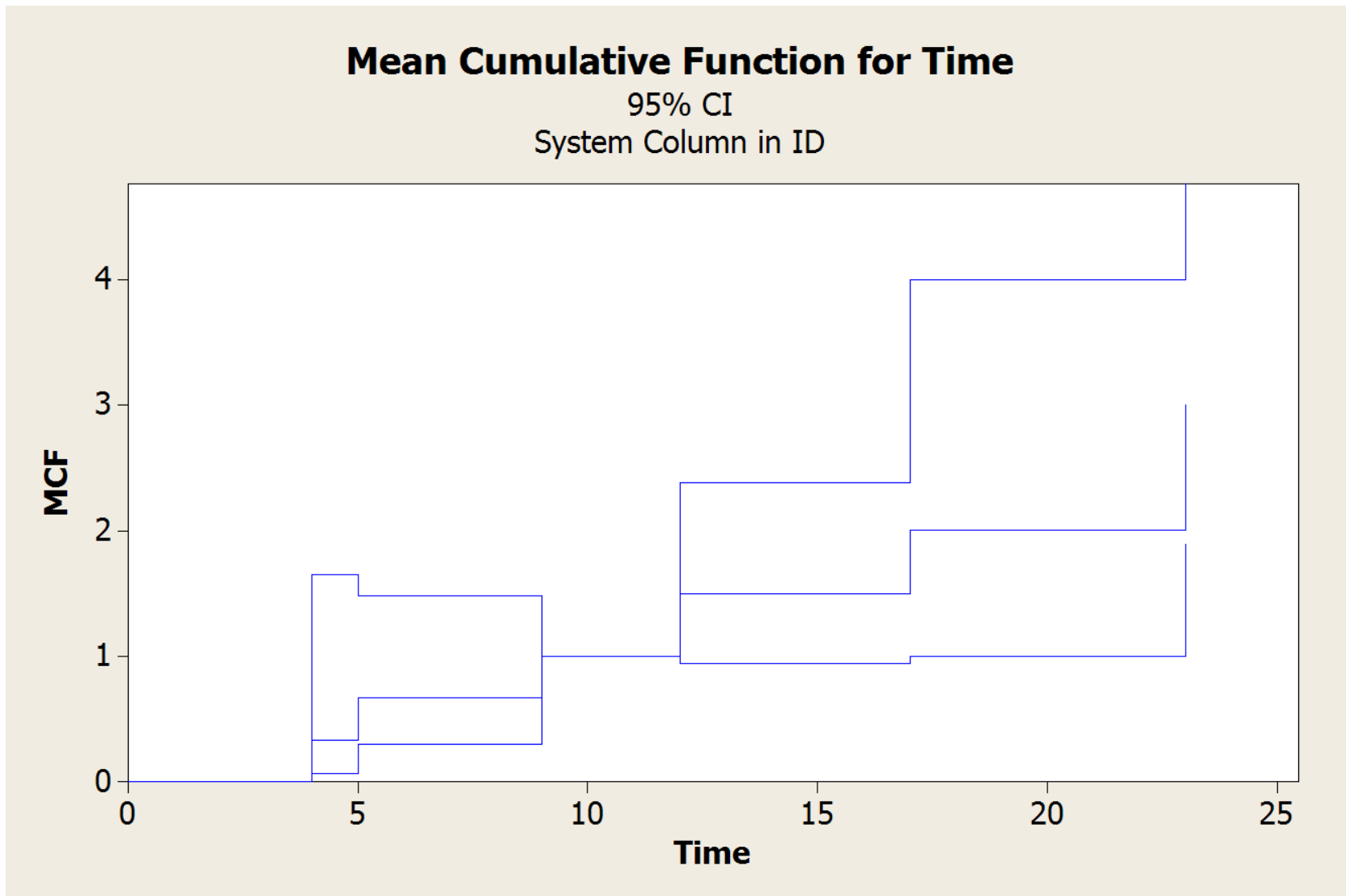
Nonparametric Growth Curve: Time System: ID

Nonparametric Estimates

Table of Mean Cumulative Function

Time	Mean		95% Normal CI		System
	Cumulative Function	Standard Error	Lower	Upper	
4	0,33333	0,272166	0,06728	1,65151	3
5	0,66667	0,272166	0,29951	1,48392	1
9	1,00000	0,000000	1,00000	1,00000	2
12	1,50000	0,353553	0,94506	2,38079	1
17	2,00000	0,707107	1,00020	3,99922	1
23	3,00000	0,707107	1,89013	4,76158	2

## Simple Example With 3 Systems



## Nelson-Aalen estimator for Cumulative ROCOF $W(t)$

1. Order all failure times as  $t_1 < t_2 < \dots < t_n$ .
2. Let  $d_j(t_i) = \#$  events in system  $j$  at  $t_i$ .
3. Let  $d(t_i) = \sum_{j=1}^m d_j(t_i) = \#$  events in all systems at  $t_i$ .
4. Let  $Y_j(t) = \begin{cases} 1 & \text{if system } j \text{ is under observation at time } t \\ 0 & \text{otherwise} \end{cases}$
5. Let  $Y(t) = \sum_{j=1}^m Y_j(t) = \#$  systems under observation at time  $t$ .

Then

Under general assumptions:  $\widehat{W}(t) = \sum_{t_i \leq t} \frac{d(t_i)}{Y(t_i)}$ .

Assuming NHPP:  $\text{Var } \widehat{W}(t) = \sum_{t_i \leq t} \frac{d(t_i)}{\{Y(t_i)\}^2}$

Under general assumptions (MINITAB):  $\text{Var } \widehat{W}(t) = \sum_{j=1}^m \left\{ \sum_{t_i \leq t} \frac{Y_j(t_i)}{Y(t_i)} \left[ d_j(t_i) - \frac{d(t_i)}{Y(t_i)} \right] \right\}^2$

Illustration of last formula for Simple NHPP Example  
 (Compare with MINITAB Output):

$$\begin{aligned}\text{Var } \widehat{W}(4) &= \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 + \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 + \left\{ \frac{1}{3} \left[ 1 - \frac{1}{3} \right] \right\}^2 \\ &= \frac{6}{81} = 0.2722^2\end{aligned}$$

$$\begin{aligned}\text{Var } \widehat{W}(5) &= \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 1 - \frac{1}{3} \right] \right\}^2 \\ &+ \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 \\ &+ \left\{ \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 \\ &= \frac{6}{81} = 0.2722^2\end{aligned}$$



$$\begin{aligned}
\text{Var } \widehat{W}(9) &= \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 \\
&+ \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 1 - \frac{1}{3} \right] \right\}^2 \\
&+ \left\{ \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 \\
&= 0
\end{aligned}$$

$$\begin{aligned}
\text{Var } \widehat{W}(12) &= \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{2} \left[ 1 - \frac{1}{2} \right] \right\}^2 \\
&+ \left\{ \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{2} \left[ 0 - \frac{1}{2} \right] \right\}^2 \\
&+ \left\{ \frac{1}{3} \left[ 1 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] + \frac{1}{3} \left[ 0 - \frac{1}{3} \right] \right\}^2 \\
&= \frac{1}{8} = 0.3536^2
\end{aligned}$$

## Simple Example With 3 Systems

Power Law NHPP Model:  $W(t; \alpha, \theta) = (t/\theta)^\alpha$

### Results for: SimpleNHPP.MTW

#### Parametric Growth Curve: Time

System: ID

Model: Power-Law Process

Estimation Method: Maximum Likelihood

#### Parameter Estimates

Parameter	Estimate	Standard Error	95% Normal CI	
			Lower	Upper
Shape	1,19423	0,445	0,323015	2,06545
Scale	11,3803	4,840	1,89335	20,8672

#### Test for Equal Shape Parameters

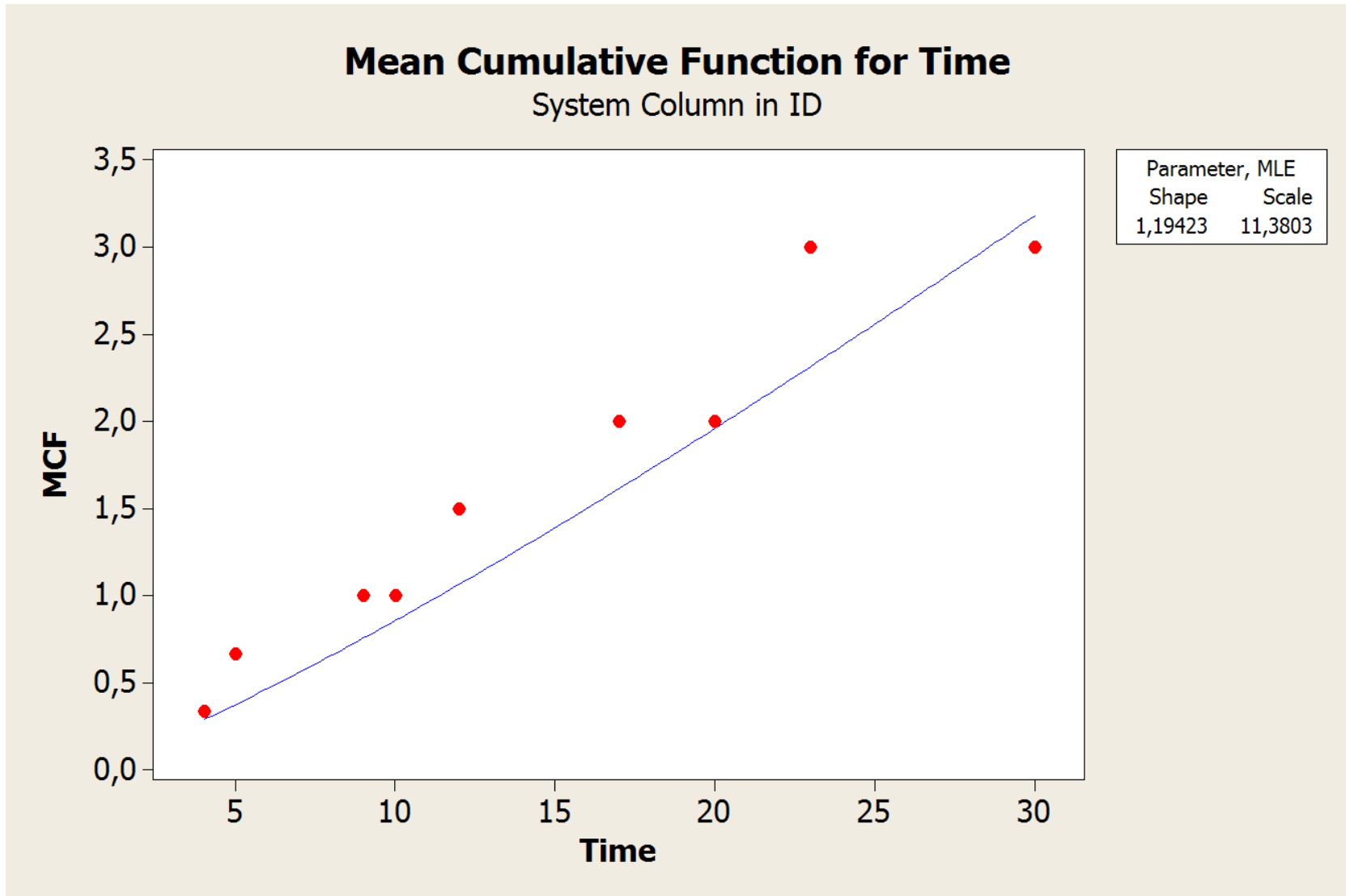
Bartlett's Modified Likelihood Ratio Chi-Square

Test Statistic	0,06
P-Value	0,972
DF	2

#### Trend Tests

Test Statistic	MIL-Hdbk-189		Laplace's		Anderson-Darling
	TTT-based	Pooled	TTT-based	Pooled	
Test Statistic	9,03	8,89	0,28	0,31	0,28
P-Value	0,599	0,576	0,781	0,756	0,954
DF	12	12			

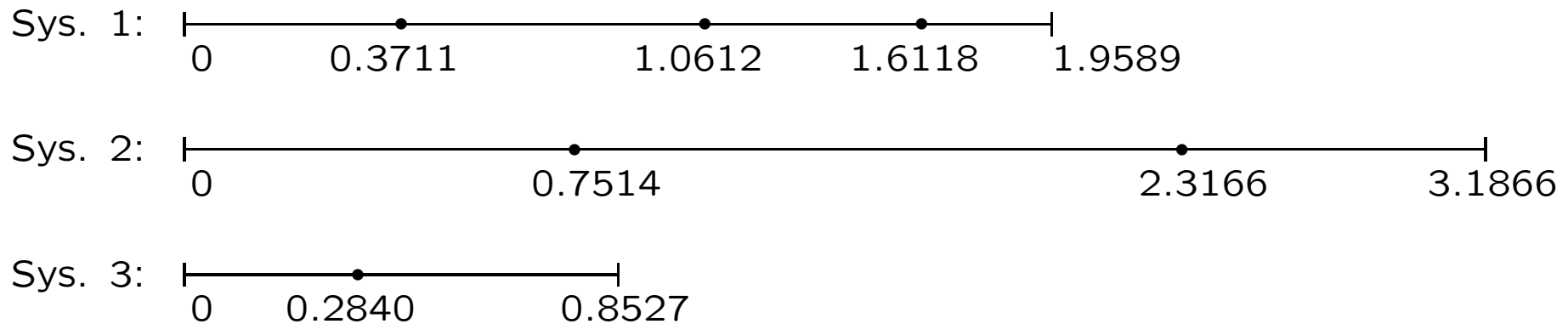
## Simple Example With 3 Systems



## RESIDUAL PROCESS: "SIMPLE EXAMPLE".

Data points (and endpoints on axes) are transformed with the estimated cumulative ROCOF,

$$\hat{W}(t) = 0.0538 \cdot t^{1.20}$$



Times between events, plus censored times at the end of each axis, are on the next slide analysed by MINITAB as a set of censored exponential variables.

MINITAB - Untitled

File Edit Manip Calc Stat Graph Editor Window Help

Session

### Distribution Analysis: C1

Variable: C1

Censoring Information	Count
Uncensored value	6
Right censored value	3
Censoring value: C2 = 0	

Estimation Method: Maximum Likelihood  
Distribution: Exponential

Parameter	Estimate	Standard Error	95,0% Lower	95,0% Upper
Shape	1,00000			
Scale	0,99999	0,4082	0,4492	2,2257

Log-Likelihood = -5,999  
Goodness-of-Fit  
Anderson-Darling (adjusted) = 4,2319

ProbPlot for C1

Probability Plot for C1  
Exponential Distribution - ML Estimates - 95,0% CI  
Censoring Column in C2

Statistic	Value
Shape	1,000
Scale	0,9999
MTTF	0,9999
StDev	0,9999
Median	0,6931
IQR	1,0985
Failure	6
Censor	3
AD*	4,2319

Worksheet 1 \*\*\*

	C1	C2	C3	C4	C5	C6
1	0,3711	1				
2	0,6901	1				
3	0,5518	1				
4	0,3471	0				
5	0,7514	1				
6	1,5652	1				
7	0,8700	0				
8	0,2840	1				
9	0,5687	0				
10						
11						
12						

Project... ProbPL...

Current Worksheet: Worksheet 1

Start | 2 Intern... | 3 matlab | WinEdt 5... | abel.math... | Foller | Yap 0.99a... | Message C... | 2 Corel... | MINITA... | 19:34

## **Valve Seat Replacement Times (Nelson and Doganaksoy 1989)**

Data collected from valve seats from a fleet of 41 diesel engines (days of operation)

- Each engine has 16 valves
- Does the replacement rate increase with age?
- How many replacement valves will be needed in the future?
- Can valve life in these systems be modeled as a renewal process?

# VALVESEAT DATA

TMA4275valveseat.MTW ***									
↓	C1	C2	C3	C4	C5	C6	C7	C8	C
	ID	Time							
1	1	761							
2	2	759							
3	3	98							
4	3	667							
5	4	326							
6	4	653							
7	4	653							
8	4	667							
9	5	665							
10	6	84							
11	6	667							
12	7	87							
13	7	663							
14	8	646							
15	8	653							
16	9	92							
17	9	653							
18	10	651							
19	11	258							
20	11	328							
21	11	377							
22	11	621							
23	11	650							
24	12	61							
25	12	539							
26	12	648							

**Nonparametric Growth Curve** [X]

Data are exact failure/retirement times  
 Data are interval failure/retirement times

Variables/  
 Start:

End:

**System Information**  
 System ID:

Number of systems:

By variable:

Retirement...  
 Cost-Freq...  
 Graphs...  
 Options...  
 Storage...

Select  
 Help  
 OK  
 Cancel

**Nonparametric Growth Curve - Retirement** [X]

Retirement time at largest time for system  
 Failure truncated systems  
 Time truncated systems  
 Retirement time defined by retirement columns

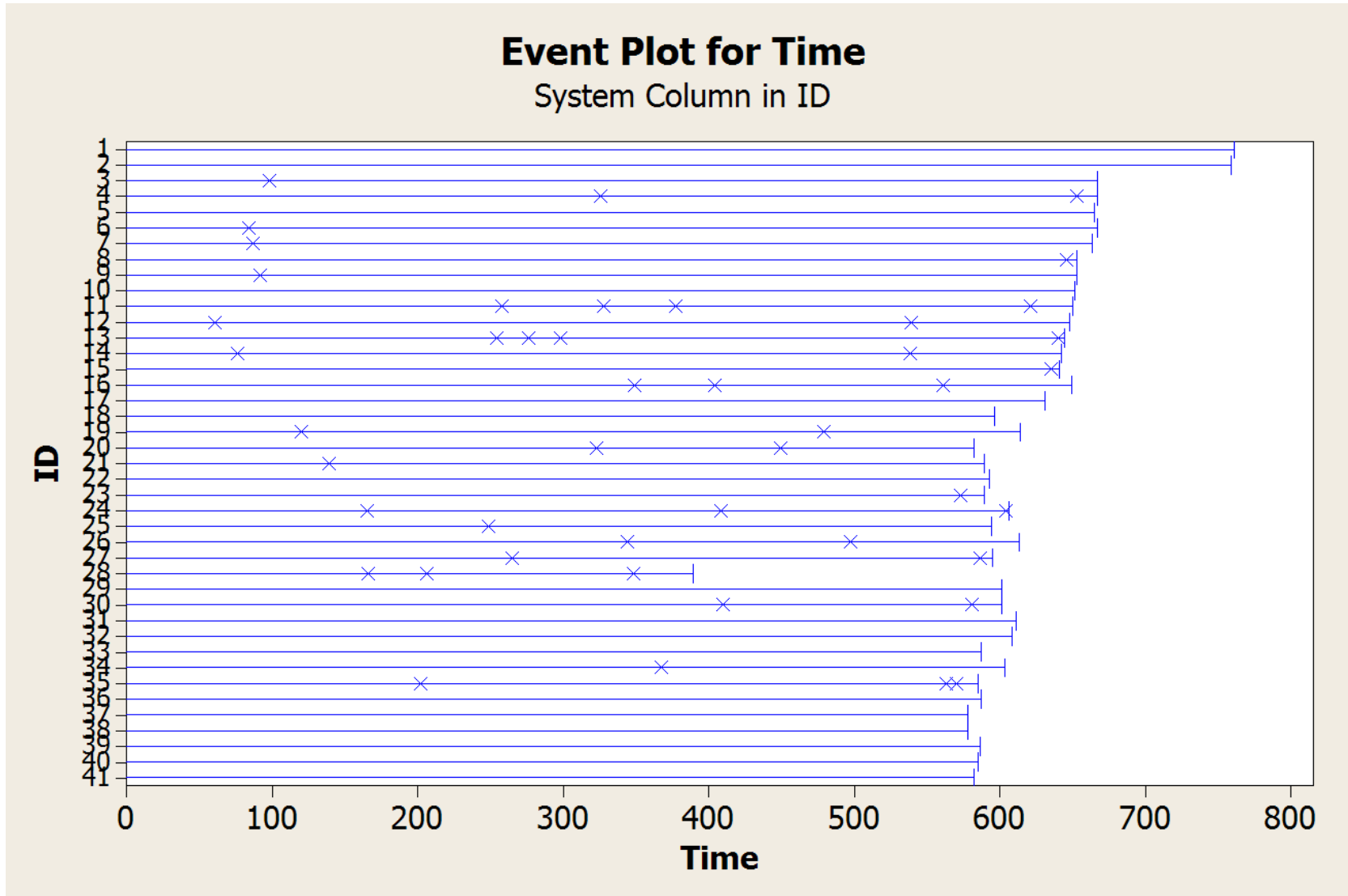
Retirement

Retirement

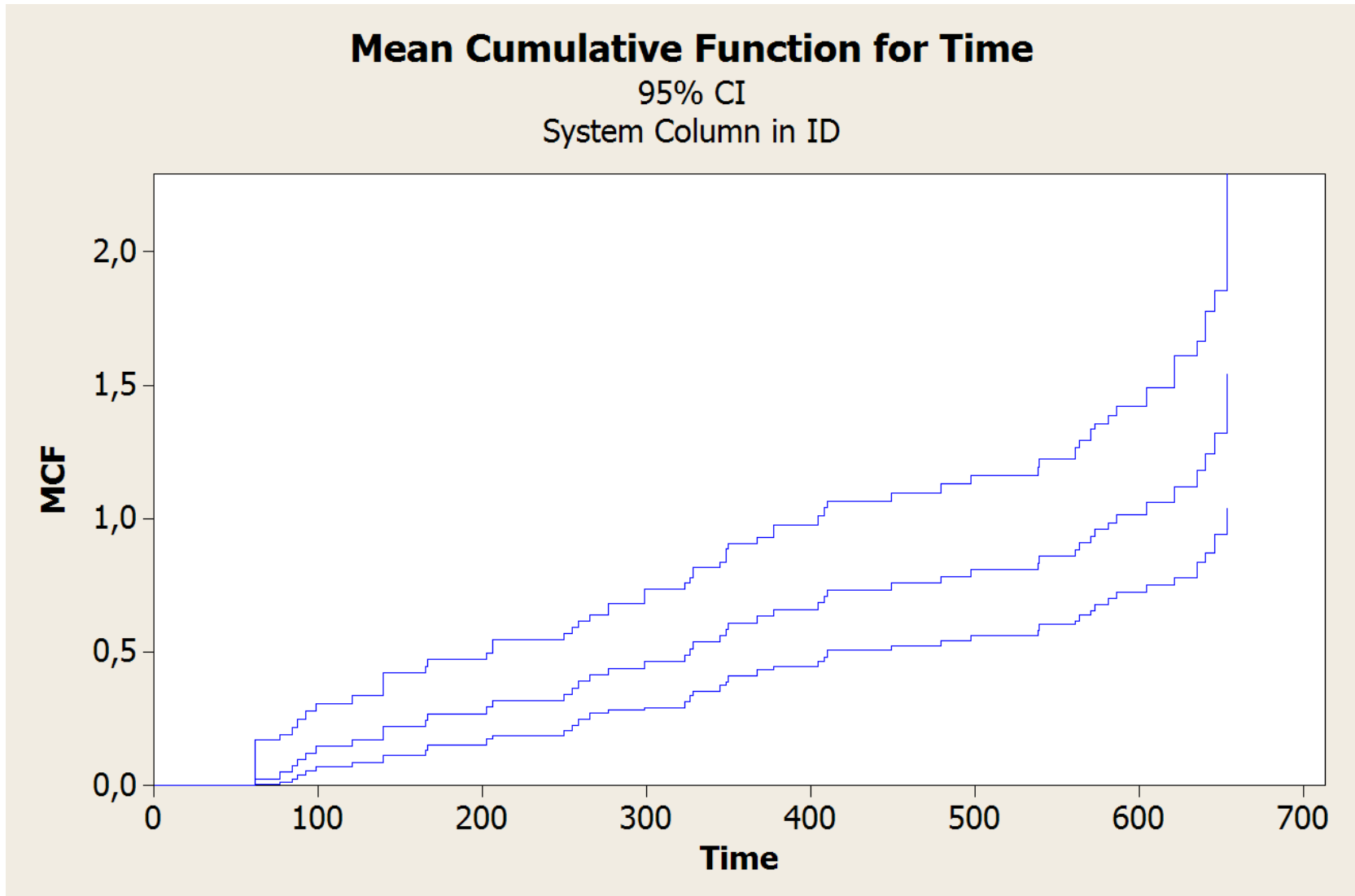
Select  
 Help  
 OK  
 Cancel



# VALVESEAT DATA



# VALVESEAT DATA



# VALVESEAT DATA

## Nonparametric Growth Curve: Time

System: ID

Nonparametric Estimates

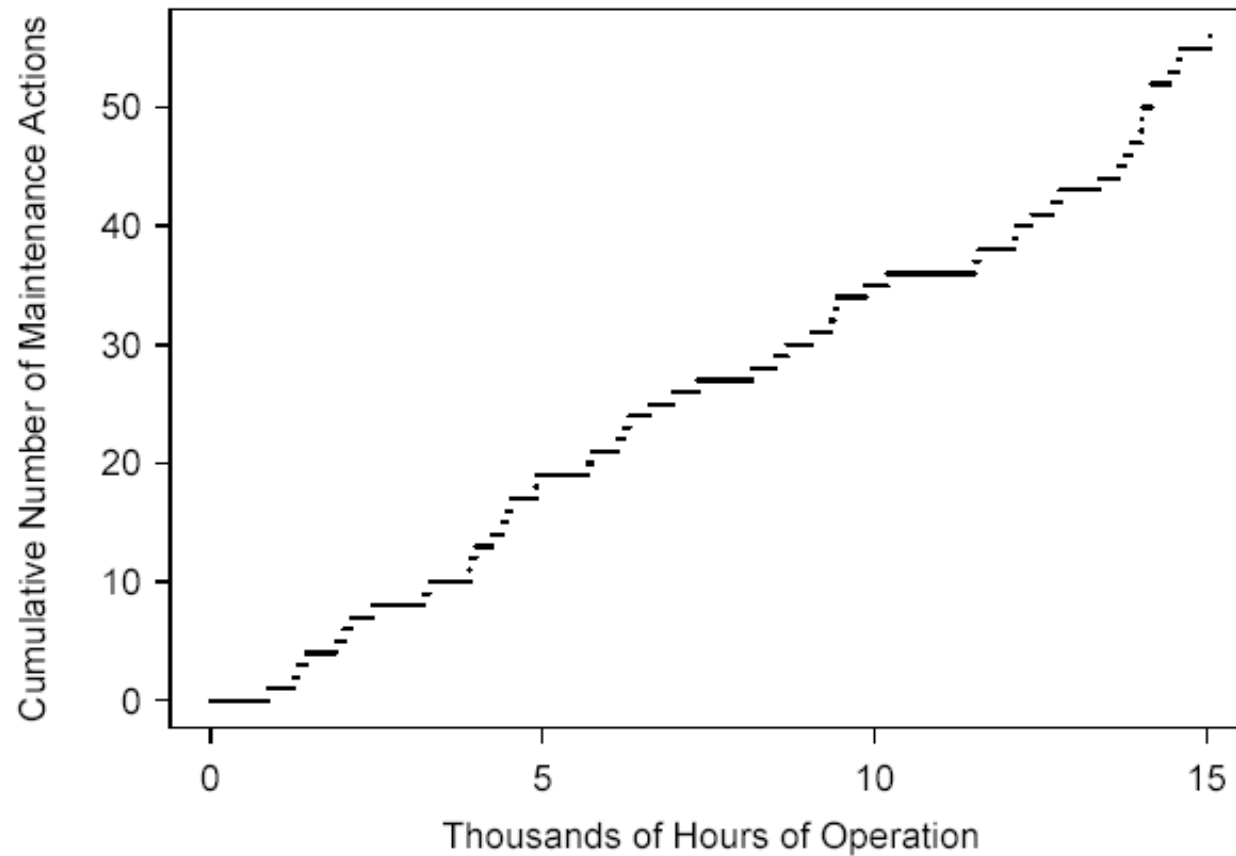
Table of Mean Cumulative Function

Time	Mean		95% Normal CI		System
	Cumulative Function	Standard Error	Lower	Upper	
61	0,02439	0,024091	0,00352	0,16903	12
76	0,04878	0,033641	0,01262	0,18848	14
84	0,07317	0,040670	0,02462	0,21750	6
87	0,09756	0,046340	0,03846	0,24750	7
92	0,12195	0,051105	0,05364	0,27726	9
98	0,14634	0,055199	0,06987	0,30650	3
120	0,17073	0,058764	0,08696	0,33519	19
139	0,19512	0,061891	0,10479	0,36333	21
139	0,21951	0,073270	0,11411	0,42226	21
165	0,24390	0,075417	0,13305	0,44711	24
166	0,26829	0,077317	0,15251	0,47196	28
202	0,29268	0,078988	0,17246	0,49672	35
206	0,31707	0,087527	0,18458	0,54467	28
249	0,34146	0,088680	0,20525	0,56807	25
254	0,36585	0,089656	0,22631	0,59143	13
258	0,39024	0,090461	0,24775	0,61468	11
265	0,41463	0,091101	0,26955	0,63780	27
276	0,43902	0,097858	0,28363	0,67955	13
298	0,46341	0,109607	0,29150	0,73671	13
323	0,48780	0,109740	0,31387	0,75812	20
326	0,51220	0,109740	0,33656	0,77949	4
328	0,53659	0,114907	0,35266	0,81643	11
344	0,56098	0,114654	0,37581	0,83737	26
348	0,58537	0,124250	0,38615	0,88737	28
349	0,60976	0,123782	0,40960	0,90772	16
367	0,63415	0,123194	0,43334	0,92801	34
377	0,65854	0,131842	0,44480	0,97498	11
404	0,68354	0,135939	0,46289	1,00936	16

## Times of Unscheduled Maintenance Actions for a USS Grampus Diesel Engine

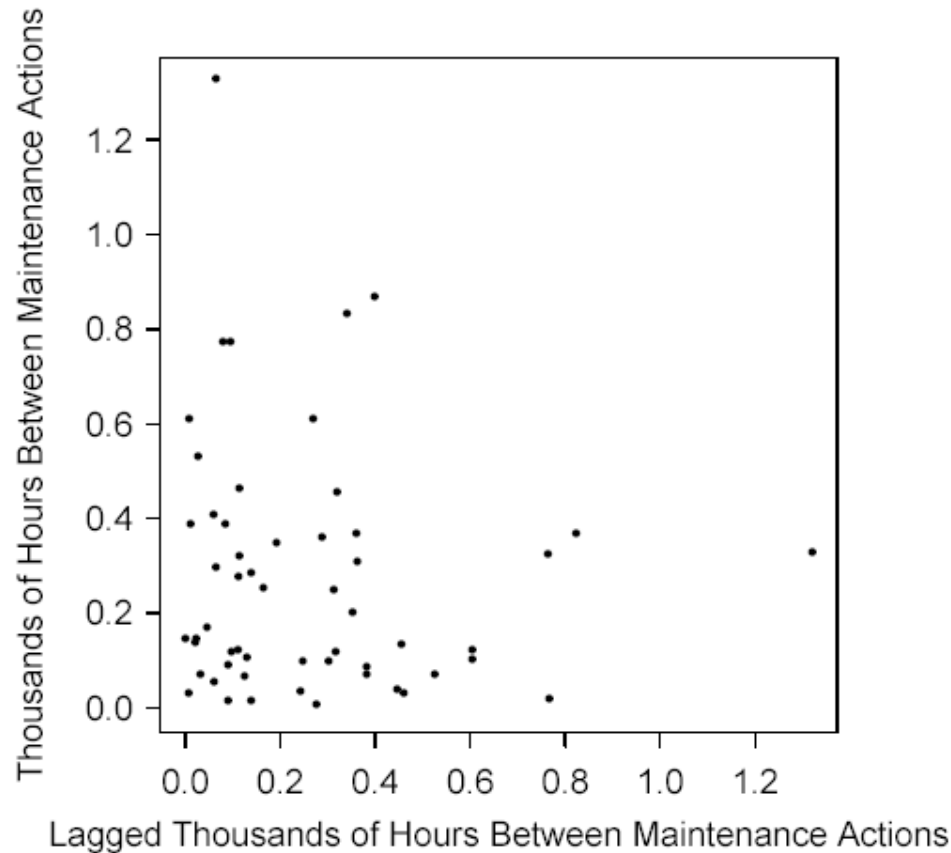
- Unscheduled maintenance actions caused by failure of imminent failure.
- Unscheduled maintenance actions are inconvenient and expensive.
- Data available for 16,000 operating hours.
- Data from Lee (1980).
- Is the system deteriorating (i.e., are failures occurring more rapidly as the system ages)?
- Can the occurrence of unscheduled maintenance actions be modeled by an HPP?

# Cumulative Number of Unscheduled Maintenance Actions Versus Operating Hours for a USS Grampus Diesel Engine Lee (1980)



Grampus- data: Plot of  $(T_i, T_{i+1})$  to investigate whether times between failures can be assumed independent. The figure does not indicate a correlation between successive times.

**USS Grampus Diesel Engine  
Plot of Times Between Unscheduled Maintenance  
Actions Versus Lagged Times Between Unscheduled  
Maintenance Actions**



## The Likelihood for the NHPP - Single Unit

- With **interval** recurrence data.

Suppose that the unit has been observed for a period  $(0, t_a]$  and the data are the number of recurrences  $d_1, \dots, d_m$  in the nonoverlapping intervals  $(t_0, t_1], (t_1, t_2], \dots, (t_{m-1}, t_m]$  (with  $t_0 = 0, t_m = t_a$ ).

$$\begin{aligned} L(\boldsymbol{\theta}) &= \Pr [N(t_0, t_1) = d_1, \dots, N(t_{m-1}, t_m) = d_m] \\ &= \prod_{j=1}^m \Pr [N(t_{j-1}, t_j) = d_j] \\ &= \prod_{j=1}^m \frac{[\mu(t_{j-1}, t_j; \boldsymbol{\theta})]^{d_j}}{d_j!} \exp [-\mu(t_{j-1}, t_j; \boldsymbol{\theta})] \\ &= \prod_{j=1}^m \frac{[\mu(t_{j-1}, t_j; \boldsymbol{\theta})]^{d_j}}{d_j!} \times \exp [-\mu(t_0, t_a; \boldsymbol{\theta})] \end{aligned}$$

## The Likelihood for the NHPP (Continued)

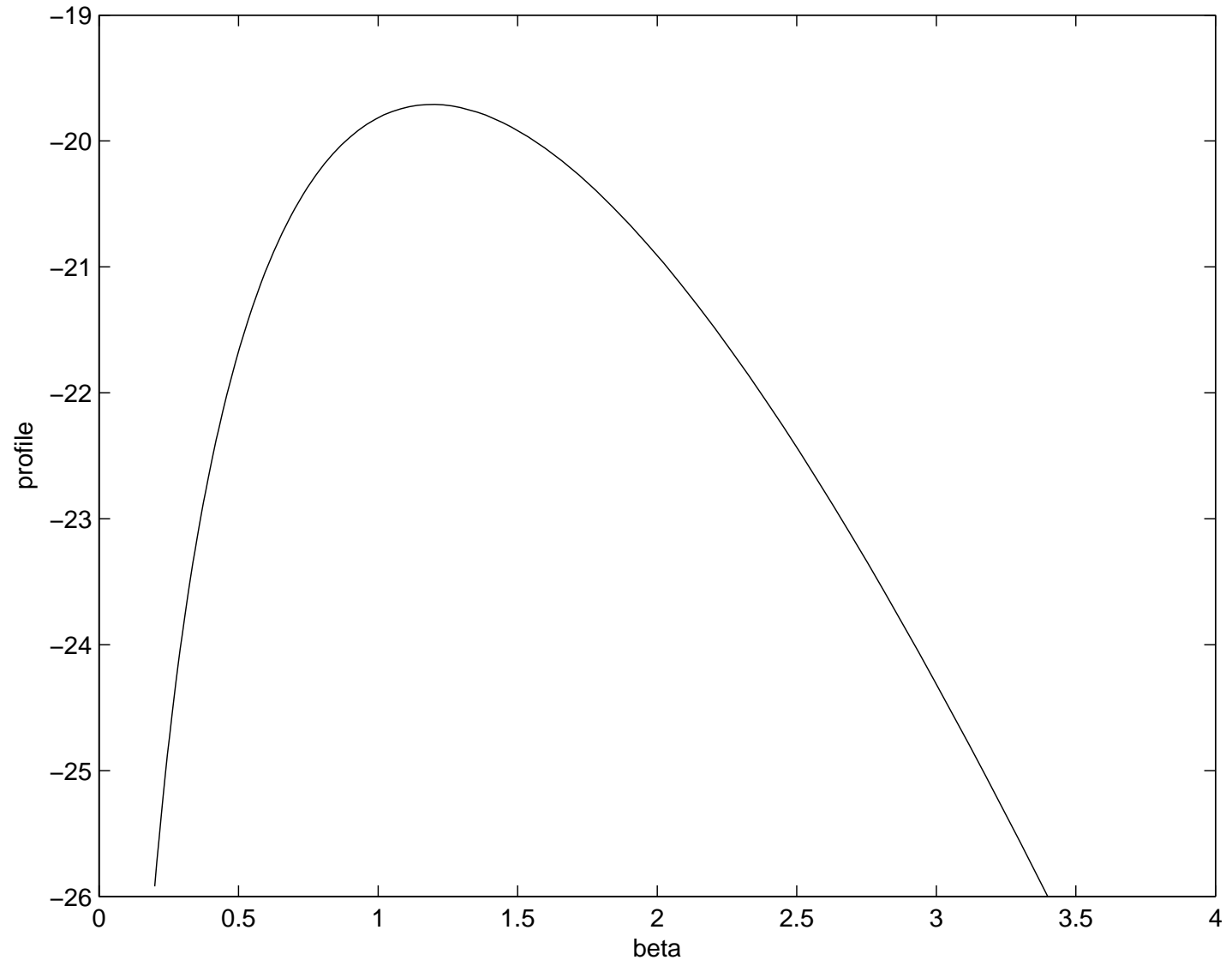
- If the number of intervals  $m$  increases and there are **exact** recurrences at  $t_1 \leq \dots \leq t_r$  (here  $r = \sum_{j=1}^m d_j$ ,  $t_0 \leq t_1$ ,  $t_r \leq t_a$ ), then using a limiting argument it follows that the likelihood in terms of the density approximation is

$$L(\boldsymbol{\theta}) = \prod_{j=1}^r \nu(t_j; \boldsymbol{\theta}) \times \exp[-\mu(0, t_a; \boldsymbol{\theta})]$$

- For simplicity, above we assumed that the intervals are contiguous. Obvious changes to the formula above give the likelihood when there are gaps among the intervals.
- In both cases (the interval data or exact recurrences data) the same methods used in Chapters 7, 8 can be used to obtain the ML estimate  $\hat{\boldsymbol{\theta}}$  and confidence regions for  $\boldsymbol{\theta}$  or functions of  $\boldsymbol{\theta}$ .

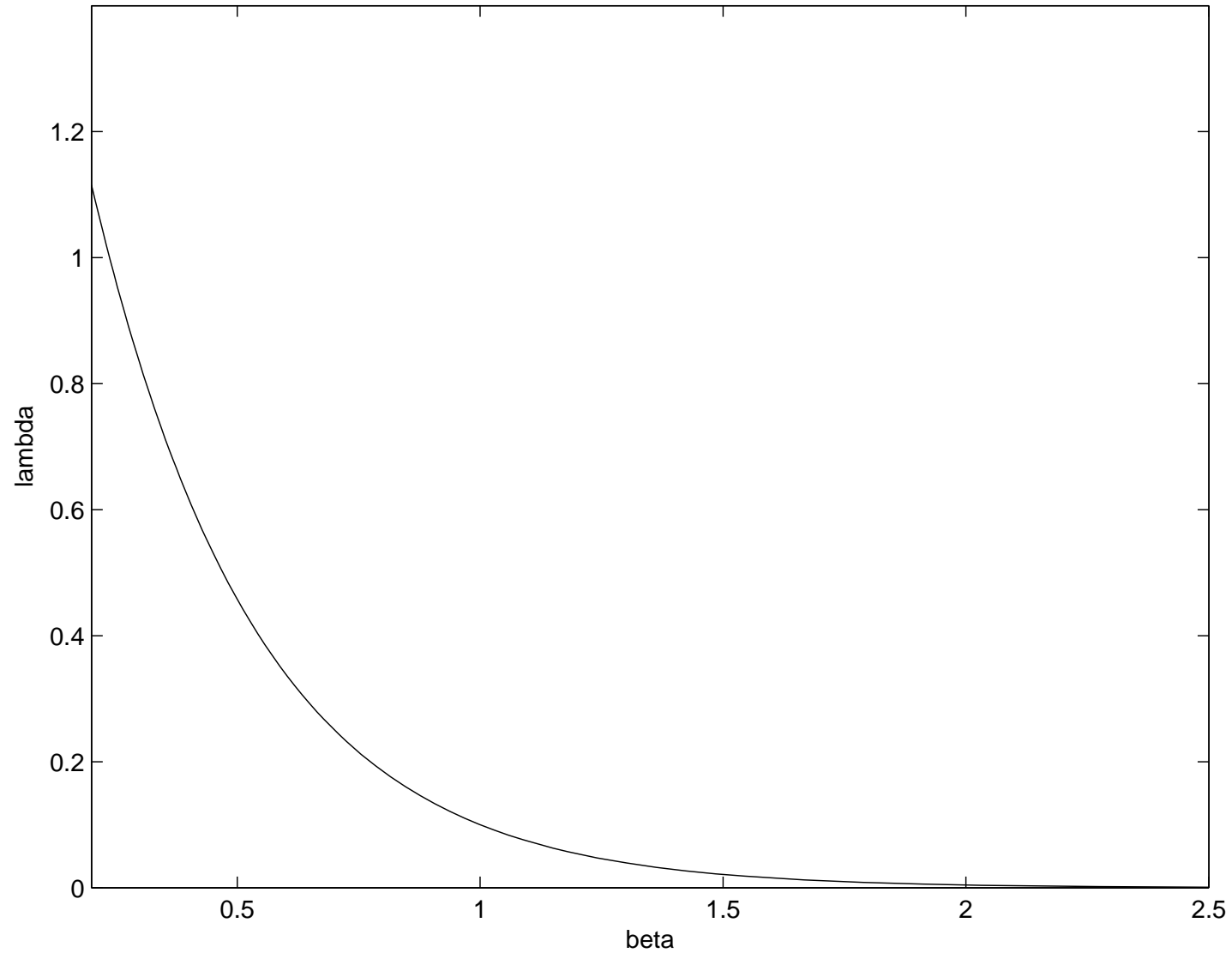


PROFILE LIKELIHOOD FOR BETA  
("SIMPLE EXAMPLE")  
 $\hat{\beta} = 1.20, \hat{\lambda} = 0.0538.$

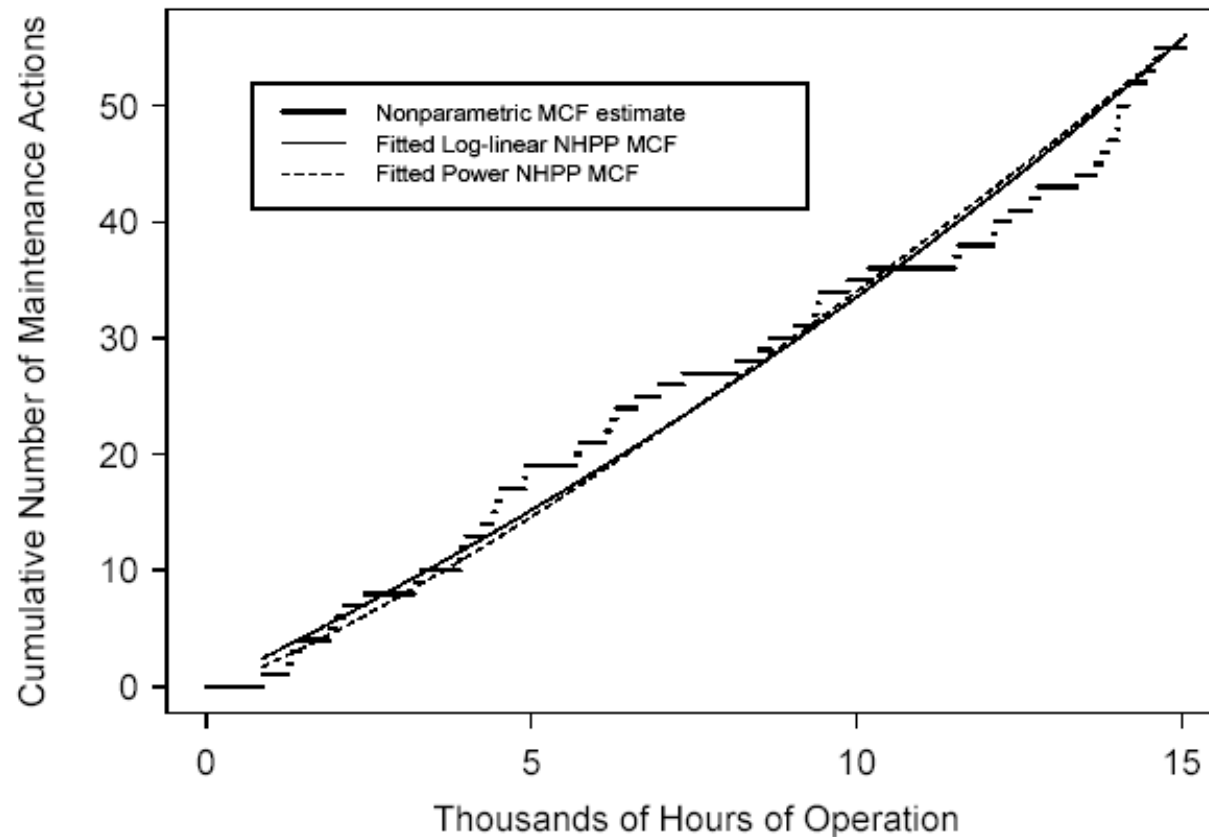


# CONNECTION BETWEEN LAMBDA OG BETA ("SIMPLE EXAMPLE")

$$\hat{\beta} = 1.20, \hat{\lambda} = 0.0538.$$



## Cumulative Number of Unscheduled Maintenance Actions Versus Operating Hours with Power and Loglinear NHPP Models for a USS Grampus Diesel Engine



## Results of Fitting NHPP Models to the USS Grampus Diesel Engine Data

- Both models seem to fit the data very well.
- For the power recurrence rate model,  $\hat{\beta}=1.22$  and  $\hat{\eta}=0.553$ .
- For the loglinear recurrence rate model,  $\hat{\gamma}_0=1.01$  and  $\hat{\gamma}_1=.0377$ .
- Times between recurrences are consistent with a HPP:
  - ▶ the Lewis-Robinson test gave  $Z_{LR} = 1.02$  with  $p$ -value  $p = .21$ .
  - ▶ the MIL-HDBk-189 test gave  $X_{MHB}^2 = 92$  with  $p$ -value  $p = .08$ .



## Comparison of trend tests

[main topic](#)

Minitab provides five trend tests for data with multiple systems: MIL-hdbk-189 (TTT-based), MIL-hdbk-189 (Pooled), Laplace's (TTT-based), Laplace's (Pooled), and Anderson-Darling. The pooled Laplace and military handbook tests reduce to their respective TTT-based tests when there is only one system. These tests behave differently under the following two circumstances:

- 1 the data follow a non-monotonic trend
- 2 the data are from heterogeneous systems

### Monotonic and non-monotonic trends

There is a trend in the pattern of times between failure if the times change in a systematic way. Trends can be:

- monotonic - times between failures are getting either consistently longer (decreasing trend) or consistently shorter (increasing trend)
- non-monotonic - times between failures alternate between increasing and decreasing trend (cyclic) or have a decreasing trend, no trend, and then increasing trend (bathtub)

The Anderson-Darling test will reject the null hypothesis in the presence of both monotonic and non-monotonic trends. The other tests will generally only detect monotonic trends. While the Anderson-Darling test is useful if you suspect the existence of a cyclic or other non-monotonic trend, the other tests are more powerful in the case of a monotonic trend.

### Homogeneous and heterogeneous systems

The null hypothesis of no trend differs slightly for the different tests:

- The null hypothesis for the pooled tests (MIL-hdbk-189 and Laplace's) is that the data come from a homogeneous Poisson processes (HPP) with a possibly different [MTBF](#) for each system. Thus, rejecting the null hypothesis means that you can definitely conclude there is a trend in your data.
- The null hypothesis for the TTT-based tests (MIL-hdbk-189, Laplace's, and Anderson-Darling) is that the data come from a homogeneous Poisson process (HPP) with the same [MTBF](#) for each system. Thus, rejecting the null hypothesis could mean that either there is a trend in your data or your data come from heterogeneous systems. Therefore, you should use TTT-based tests only when you are confident that your systems are homogeneous.

The table below summarizes the different null hypotheses associated with the trend tests.

	MIL-hdbk-189 (Pooled)	MIL-hdbk-189 (TTT-based)	Laplace's (Pooled)	Laplace's (TTT-based)	Anderson- Darling
<b>Null Hypothesis</b>	HPP (possibly different MTBFs)	HPP (equal MTBFs)	HPP (possibly different MTBFs)	HPP (equal MTBFs)	HPP (possibly different MTBFs)
<b>Rejecting <math>H_0</math> means...</b>	monotonic trend	monotonic trend or systems are heterogeneous	monotonic trend	monotonic trend or systems are heterogeneous	monotonic trend or non-monotonic trend or systems are heterogeneous

See [\[12\]](#) for more information concerning these tests.



# TTT-based tests for trend in repairable systems data

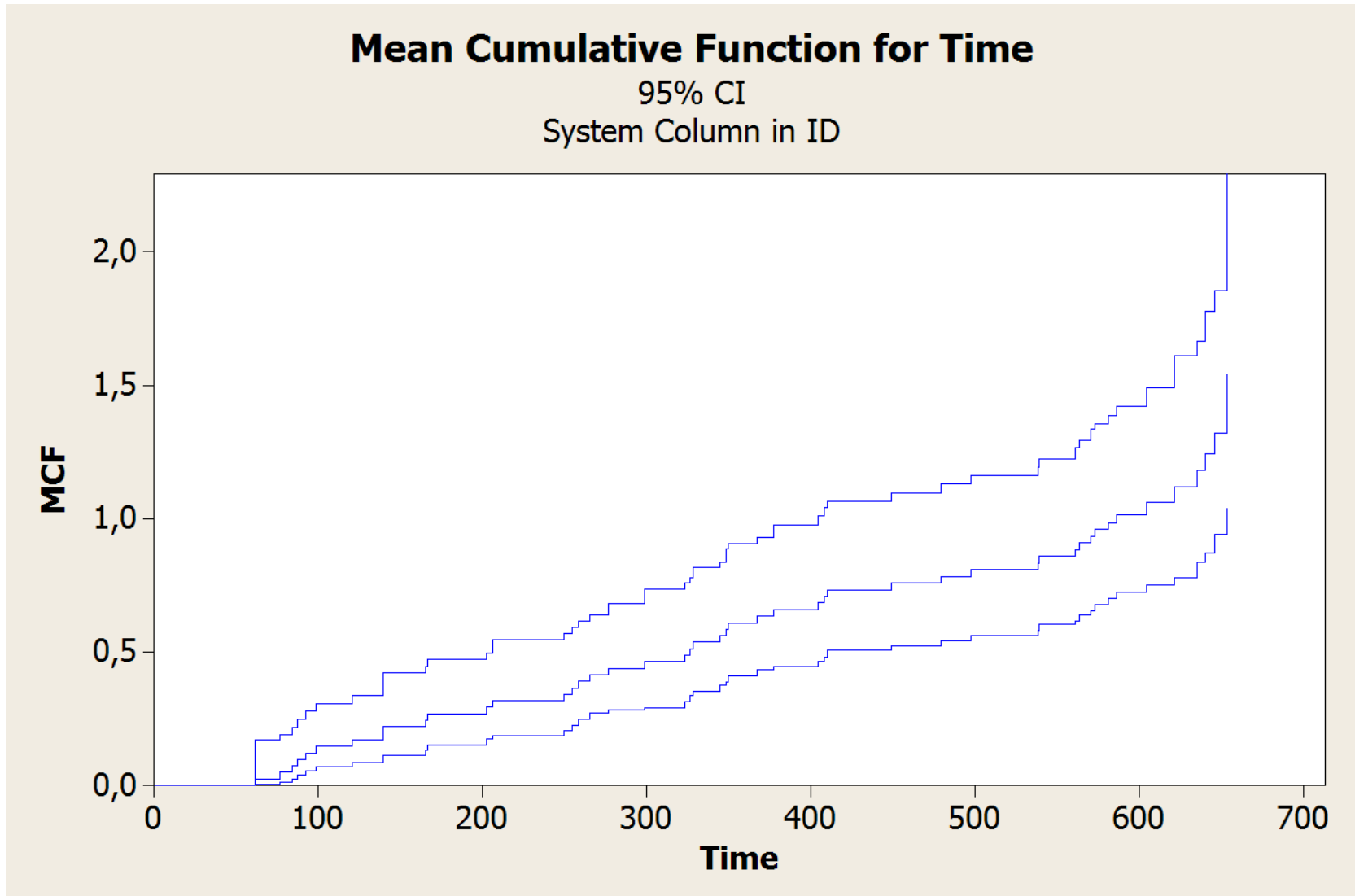
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A major aspect of analysis of failure data for repairable systems is the testing for a possible trend in interfailure times. This paper reviews some important and popular graphical methods and tests for the nonhomogeneous Poisson process model. In particular, the total time on test (TTT) plot is considered, and trend tests based on the TTT-statistic are motivated and derived. In particular, a test based on the Anderson–Darling statistic is suggested. The tests are evaluated and compared in a simulation study, both with respect to the achievement of correct significance level and rejection power. The considered alternatives to ‘no trend’ are the log-linear, power law and a class of bathtub-shaped intensity functions. The simulation study involves single systems, as well as the case where several independent systems of the same kind are observed. © 1998 Elsevier Science Limited.

# Valveseat Data



## Valveseat Data

### Trend Tests

	MIL-Hdbk-189		Laplace's		Anderson-Darling
	TTT-based	Pooled	TTT-based	Pooled	
Test Statistic	80,28	66,15	0,46	2,38	0,80
P-Value	0,249	0,017	0,645	0,017	0,478
DF	96	96			



## TTT-analysis Simple Example

Row	STTT	ID	Scaled
1	12	1	0,20000
2	15	1	0,25000
3	27	1	0,45000
4	34	1	0,56667
5	44	1	0,73333
6	53	1	0,88333
7	60	1	1,00000

### Parameter Estimates

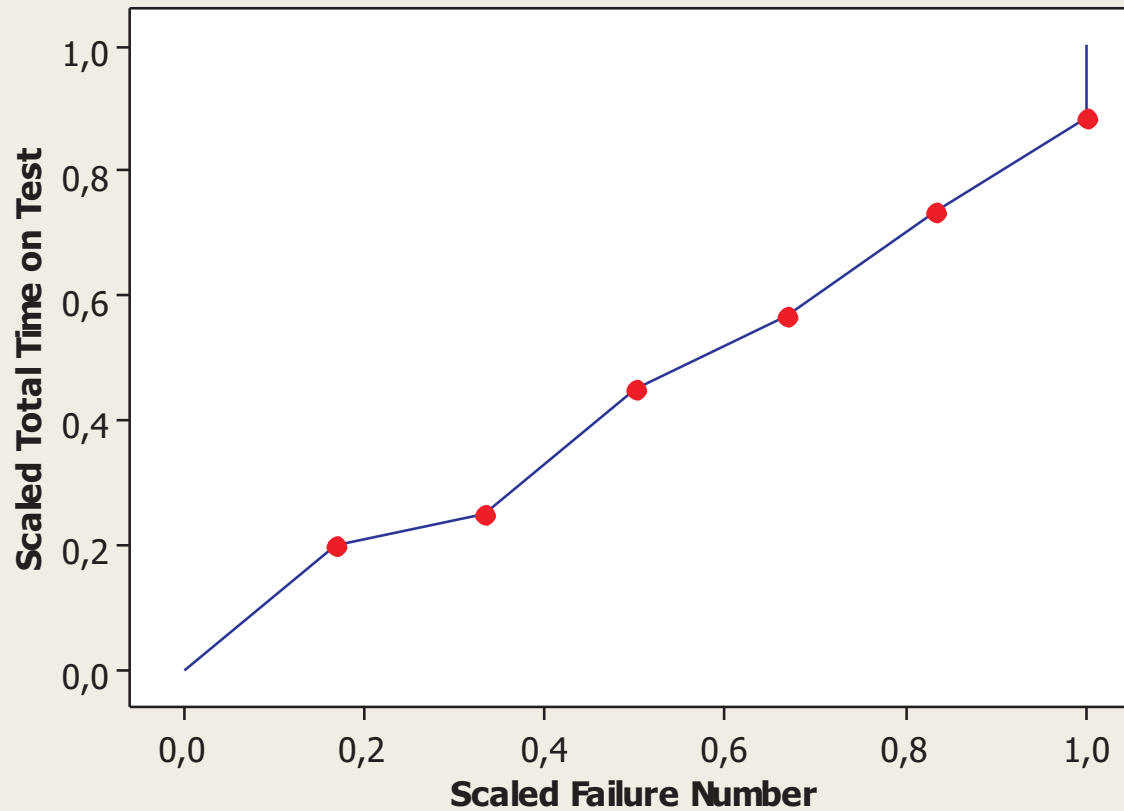
Parameter	Estimate	Standard Error	95% Normal CI	
			Lower	Upper
Shape	1,25093	0,511	0,249996	2,25186
Scale	0,238749	0,160	-0,0746105	0,552109

### Trend Tests

	MIL-Hdbk-189	Laplace's	Anderson-Darling
Test Statistic	9,59	0,12	0,24
P-Value	0,697	0,906	0,977
DF	12		

### Total Time on Test Plot for Simple Example

System Column in ID



Parameter, MLE	
Shape	Scale
1,25093	0,238749

## TTT-analysis of Valve Seat Data

Parametric Growth Curve: C1

Model: Power-Law Process

Estimation Method: Maximum Likelihood

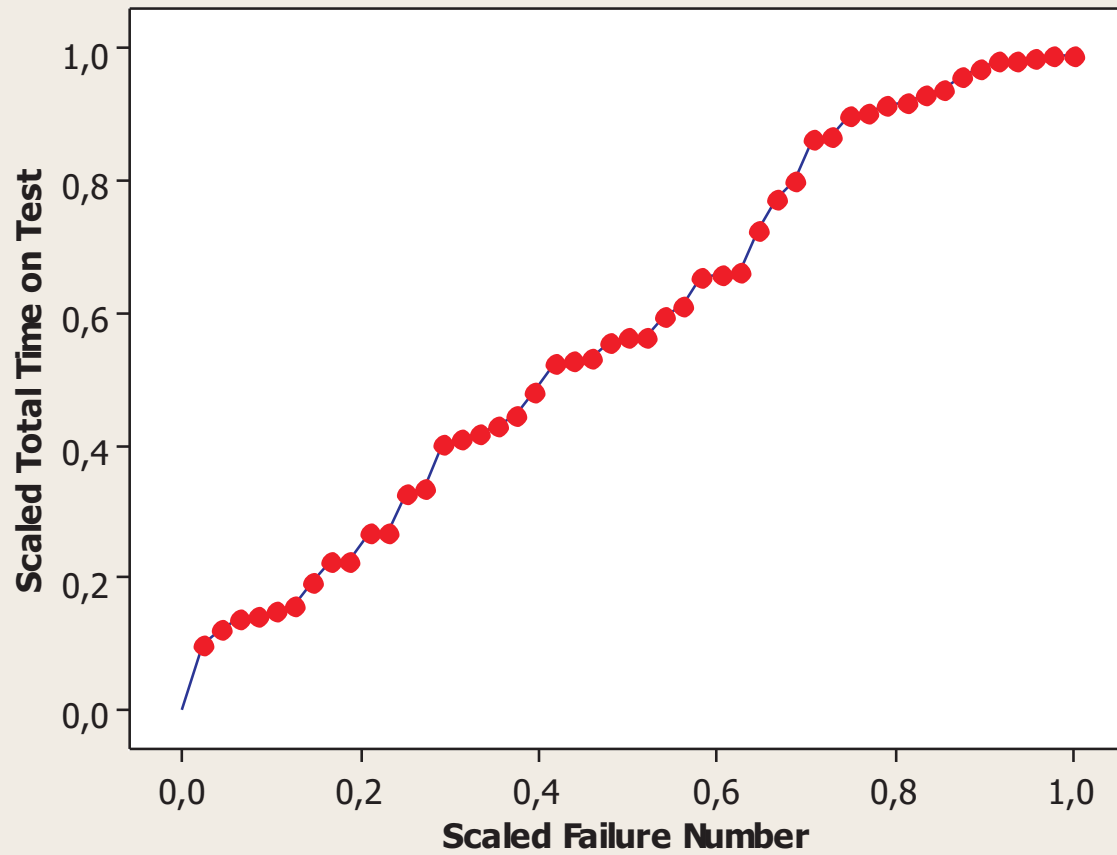
### Parameter Estimates

Parameter	Estimate	Standard Error	95% Normal CI	
			Lower	Upper
Shape	1,39706	0,202	1,00184	1,79229
Scale	0,0626023	0,026	0,0119179	0,113287

### Trend Tests

	MIL-Hdbk-189	Laplace's	Anderson-Darling
Test Statistic	68,72	2,03	3,17
P-Value	0,032	0,043	0,022
DF	96		

**Total Time on Test Plot for Valve Seat Data**



Parameter, MLE	
Shape	Scale
1,39706	0,0626023