

# Parts Counts and Reliability Prediction

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Using OTHER people's numbers can often mean you model a product  
OTHER than yours



## Workbook

Presented by

**Dr Chris Jackson**

Reliability engineer



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# Who is your teacher? ... Dr Chris Jackson

Dr Jackson holds a Ph.D. and MSc in Reliability Engineering from the University of Maryland's Center of Risk and Reliability. He also holds a BE in Mechanical Engineering, a Masters of Military Science from the Australian National University (ANU) and has substantial experience in the field of leadership, management, risk, reliability and maintainability. He is a Certified Reliability Engineer (CRE) through the American Society of Quality (ASQ) and a Chartered Professional Engineer (CPEng) through Engineers Australia.

Dr Jackson is the cofounder of [www.is4.com](http://www.is4.com) online learning, was the inaugural director of the University of California, Los Angeles (UCLA's) Center of Reliability and Resilience Engineering and the founder of its Center for the Safety and Reliability of Autonomous Systems (SARAS). He has had an extensive career as a Senior Reliability Engineer in the Australian Defence Force, and is the Director of Acuitas Reliability Pty Ltd.

He has supported many complex and material systems develop their reliability performance and assisted in providing reliability management frameworks that support business outcomes (that is, make more money). He has been a reliability management consultant to many companies across industries ranging from medical devices to small satellites. He has also led initiatives in complementary fields such as systems engineering and performance-based management frameworks (PBMFs). He is the author of two reliability engineering books, co-author of another, and has authored several journal articles and conference papers.



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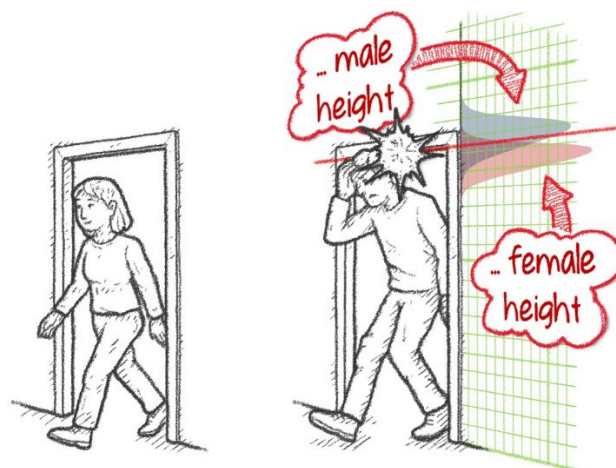
Having an 'indicative' understanding of product or system **reliability** early in the design process can help make important decisions, including (but not limited to) comparing technologies, baseline spear analysis, and so on. There are many subsystems that perform the same **function**, including mechanical, mechatronic, and computer numerically controlled (CNC). Each has its own benefits and issues, including **reliability**. Knowing that a mechanical subsystem will likely be an order of magnitude more **reliable** than other technologies might lead to that subsystem being chosen.

This need for a preliminary understanding of **reliability** often leads designers and engineers to seek 'generic' **reliability** data on components. However, this often leads to an over-reliance on external data and numbers, creating a façade of robustness without any analysis of the actual product or system being designed.

### ... think about the height of a doorway

Designing a 'doorway' that allows people to pass from one side of a wall to the other is relatively 'simple' in that only two basic dimensions need to be provided – height and width. Excessively high doorways are more expensive because they require more framing material and often require a raised ceiling. So doorways need to be 'high enough' but no higher.

One widely available statistic is the global average or mean height – 165 cm or 5' 5". However, if the door is made to be 165 cm or 5' 5" high, around half of all people walking through that doorway will hit their head. This is because the heights of females and males are not only distributed across a range of values, but are also distributed differently from each other (that is, males tend to be taller than females).



Optimizing door height should be based on accepting the **risk** that an appropriately small number of people will hit their heads as they walk through the doorway. To understand this, we need to understand the overall **distribution** of combined human heights (including both genders). This allows us to work out 'how much beyond' the mean or average height our doorway needs to be. However, a 'generic' understanding of even basic things like human height still might lead to

undesirable outcomes. For example, global **distributions** of human heights don't apply to professional basketball players (who are generally very tall) or people from Timor-Leste (who are often very short).

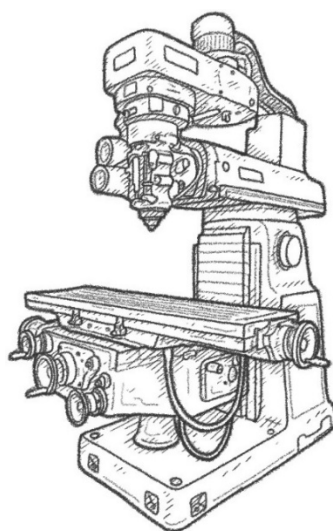


Without taking the time to understand the unique characteristics of 'your' people, you will either create a doorway that is not high enough (too many basketballers will hit their heads), or too high (doorways in Timor-Leste costing more money for no benefit).

### ... 'generic' reliability estimates

A similar issue applies to 'generic' characterizations of product and system **reliability**. **Reliability** is often based on 'smart' design, maintenance strategies, installation quality, correct environmental selection, and several other factors that make 'your' scenario unique. Relying on 'generic' characterizations of **reliability** usually chronically overestimates the **reliability** of some components and underestimates the **reliability** of others.

Consider the development of a complex product, like a commercial milling machine (illustrated below).



Even milling machines, which are 'fundamentally simple' in their function (use a rotating cutting tool to remove material from a stationary or moving workpiece), are becoming increasingly sophisticated. By extension, their designs are becoming more complex, and customers are expecting more from them.

A key component is the bearing that supports the rotating shaft that drives the cutting tool. **Reliability** or **parts prediction tables** can be found through basic online searches, which typically list **failure rate** estimates based on item category or classification. A very simplified example is illustrated below.

ITEM	FAILURE RATE
ACTUATOR	4.3085C
BEARING EMBLY	1.1077C
EMBL	129.737
CABLE ASSEMBLY	14.38%
CONNECTOR	78.6824
FAN (COOLING)	9.00712

Some online tables allow a rudimentary interrogation of the data used to generate the **failure rate** estimates. A simplified example of ball bearings is illustrated below.

ITEM	FAILURE RATE	# FAILED	DURATION	SOURCE
<input checked="" type="radio"/> BALL BEARING	1.1077C			
	0.0245			
	<1.2697	0	788 022	NPRD
	4.4444	2	450 000	SLPD
	3.4569			
	2.5000			
	<1.2500	0	800 000	AKRP
	...			

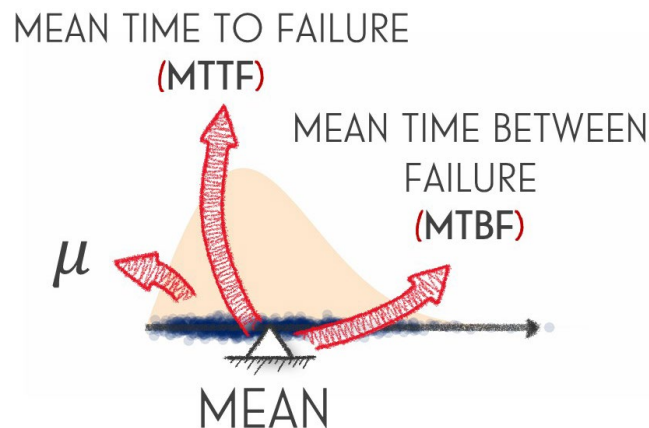
The example above illustrates a typical list of data comprising simple **failure rate** estimates ... the number of observed **failures** over a given duration ... along with references to the sources. As a rule, these data lists do not contain many **failure data points** (if any). Furthermore, the context of each data set cannot be further investigated (to identify the type of ball bearing, whether it was used in a harsh environment, and so on).

... 'how' things fail ...

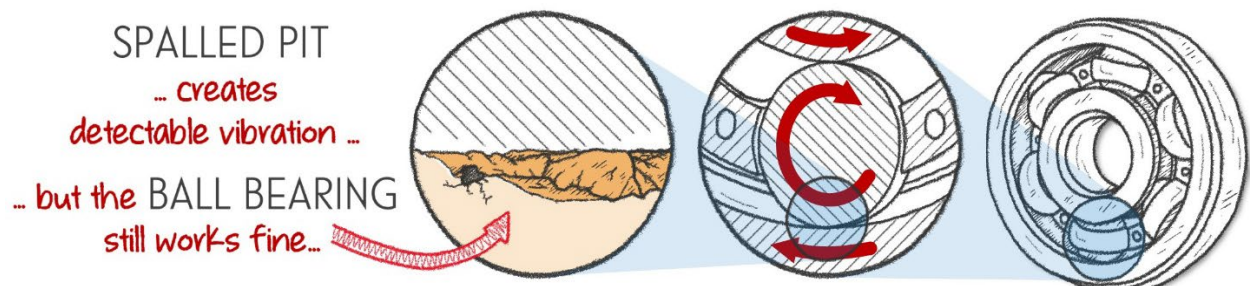
Ball bearing **failure** is contingent on many factors, including (in order of diminishing influence) particle contamination, misalignment, disassembly damage, insufficient lubrication, humidity-

induced corrosion, excessive loads, and manufacturing defects. All but manufacturing defects are controlled by the operators and designers responsible for the use and care of ball bearings.

These factors combine to create a unique '**statistical signature**' not only for ball bearings generally, but also for specific types of ball bearings used in specific ways. The typical '**statistical signature**' of ball bearings is illustrated by the **probability density curve** below, which is perfectly balanced around the **mean (time to failure)**.

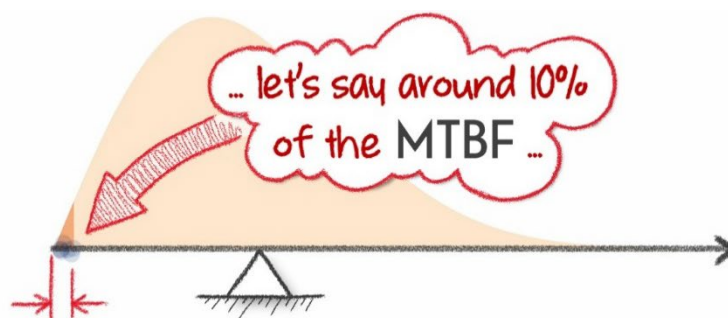


The **statistical signature** is based on 'how' ball bearings **fail**, which typically involves **spalling** (a bearing-specific type of **fatigue**) that results in pits being developed along the inner and outer races.



One maintenance strategy (#1) could be to **run all ball bearings until failure**. That is, the milling machine is designed so its ball bearings never need to be replaced, meaning they generally last as long as the milling machine's service life.

However, the knowledge of ball bearing **failure** discussed above also helps develop a **preventive maintenance (PM)** strategy (#2) in which ball bearings are replaced 'en masse' at fixed intervals. An example **PM interval-based** is illustrated below.



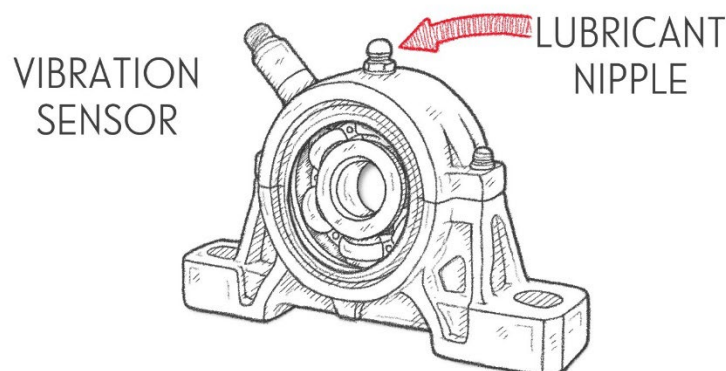


This means that every bearing will be replaced (if it has not already **failed**) after it has completed 10 % of its '**MTBF cycles**.' This is not an unusual interval scale and prevents a large number of **wear-out failures**.

Another more sophisticated **predictive maintenance (PredM)** strategy (#3) can use vibration from spalled pits to provide early warning of failure. The benefit of **PredM** is that it maximizes the useful lives of each bearing without risking the discarding of otherwise good bearings at arbitrary **PM intervals**.



These **maintenance strategies** apply to a ball bearing, like the one illustrated below in a mount contained within the milling machine.



Let's say that the ball bearing in question has an actual **failure rate** of 1.1077 failures per million cycles. This is somewhat of a misnomer, as the **failure rate** of a component that wears out over time increases. So when the **failure rate** is quoted, it often refers to the '**average**' **failure rate** for the entire life of a component. And this allows us to calculate the following ...

$$MTBF = \frac{1}{(\text{average}) \text{ failure rate}} = \frac{1}{1.1077 \text{ failures per million cycles}}$$

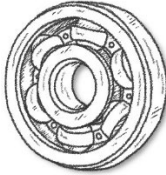
$$= 0.9027 \text{ million cycles} = 902\,700 \text{ cycles}$$

While (**average**) **failure rate** and **MTBF** above might be 'true' **reliability** characteristics of the ball bearing, this will always change if the way it is treated changes. For example, if the operator

doesn't continually add lubricant, or the lubricant is contaminated, the ball bearing will **fail** more often. Let's say that using contaminated lubricant increases the (average) **failure rate** to 3.4590 failures per million cycles.

Let's also say that a proactive operator not only lubricates the ball bearing well, but also wants to implement a fixed **PM interval** of 10 % of the **MTBF**. This means that after every 90 270 cycles (10 % of the **MTBF**), all ball bearings are replaced en masse. This decreases the **failure rate** to **0.2997 failures per million cycles** (a 73 % improvement), but also increases the **replacement rate** to **11.1978 bearings per million cycles** (10.11 times as many). This is because working ball bearings that are removed at the **PM interval** are discarded.

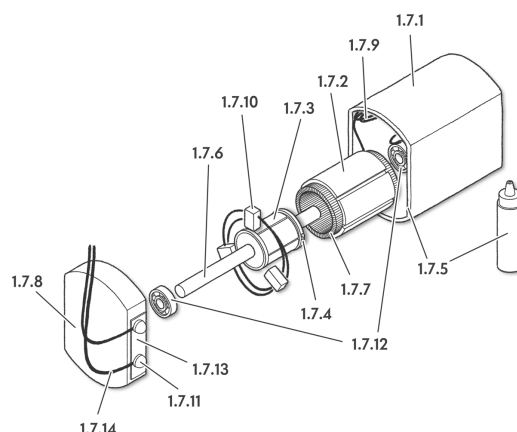
If this replacement rate is too high, or incurs too many costs, a **PredM strategy** can be employed where (for example) vibration analysis allows us to replace ball bearings at 95 % of their eventual **time-to-failure**. This results in a replacement rate of 1.1662 ball bearings **per million cycles** (5.5 % increase), but next to no **failures**. So, depending on our **maintenance strategy**, the **failure** and **replacement rates** (parts count) can vary wildly.

	FAILURE RATE	PARTs COUNT
	1.1077	1.1077
	3.4589	3.4589
	0.2997	11.1978
	... around 0	1.1662

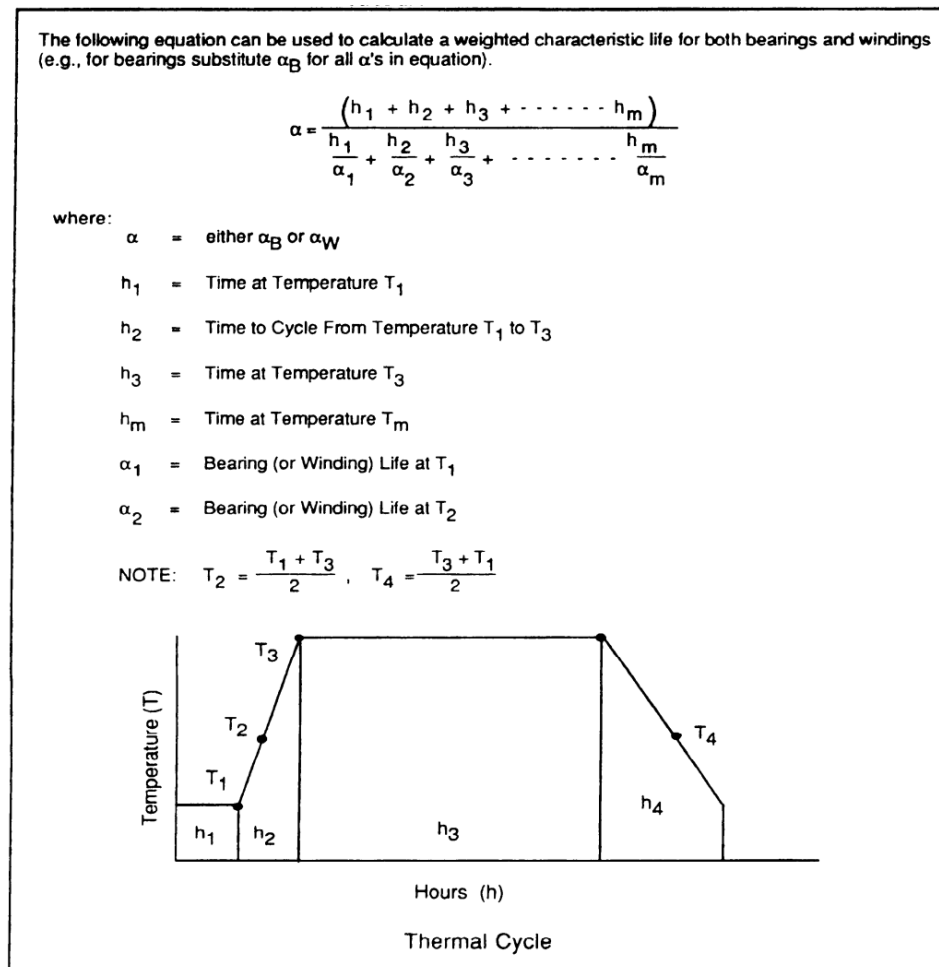
When it comes to 'generic' **reliability** tables, it is not clear where the data comes from, what **maintenance strategies** the organization that created this data was using, and (perhaps most importantly) what **maintenance strategy** you intend to use for your ball bearings or other components.

... the FAÇADE of robustness ...

Many 'generic' **reliability** tables can be found in guidebooks that include procedures and rules that appear complex and thorough. For example, electric motors include bearings and windings (as shown below).



**Military Handbook (MIL-HDBK) 217F – Reliability Prediction of Electronic Equipment** is a guidebook published by the US Department of Defense in 1990. It contains the following page that is intended to help predict the **time-to-failure** of an electric motor.



The page describes how an engineer is supposed to understand the electric motor's temperature profile, and how these different temperatures can be used to help predict **time-to-failure**. The equation of the top of the page above is as follows:

$$\alpha = \frac{h_1 + h_2 + h_3 + \dots + h_m}{\frac{h_1}{\alpha_1} + \frac{h_2}{\alpha_2} + \frac{h_3}{\alpha_3} + \dots + \frac{h_m}{\alpha_m}}$$

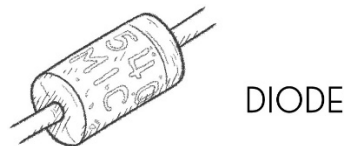
Essentially,  $h_i$  and  $\alpha_i$  are the time spent and bearing (or winding) life for a specific temperature  $T_i$ . There are several issues with describing the future life of an electric motor with this level of precision, but the most significant one is that the equation above is a **rule**. A **rule** is used to describe a relationship that is not a theory, has never been proven, and will not be found in any textbook.

Further, the bearing (or winding) lives for each temperature require further evaluation based on another range of assumptions and rules. Engineers will have invested a significant amount of time evaluating these equations and researching these values, so they often feel that their answers are precise and accurate, when they are at best estimates utilizing unproven **rules**.

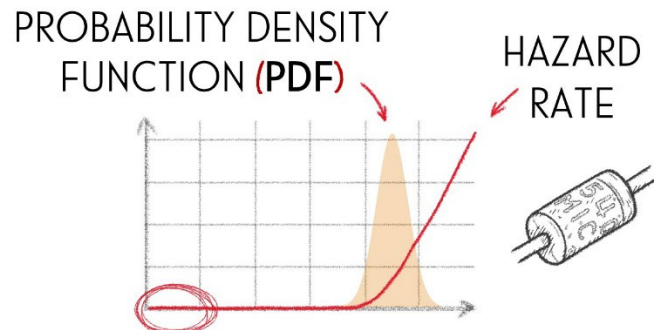
... but there is WAY more ...

Many engineers believe that there is some sort of 'steady state' that components achieve after they move through 'infant mortality.' This 'steady state' window is also assumed to have a **constant hazard** or **failure rate**, where the component doesn't **wear out**. This assumption is almost always incorrect.

For example, **MIL-HDBK 217F** contains several **failure rates** for different types of electrical components, such as diodes (which are silicon-based semiconductors that allow current to flow only in one direction).



**MIL-HDBK 217F** includes a value of **0.0038 failures per million hours** for this diode. This implies an **MTBF that exceeds 30,000 years** (which is clearly not possible). One of the reasons that this (and other electrical components) have absurd '**generic**' **failure rates** is that data is often selectively used based on the age of the components. Most electrical components are tested 'early' in their life (circled below), which doesn't capture how damage accrues and increases the **hazard** or **failure rate**.



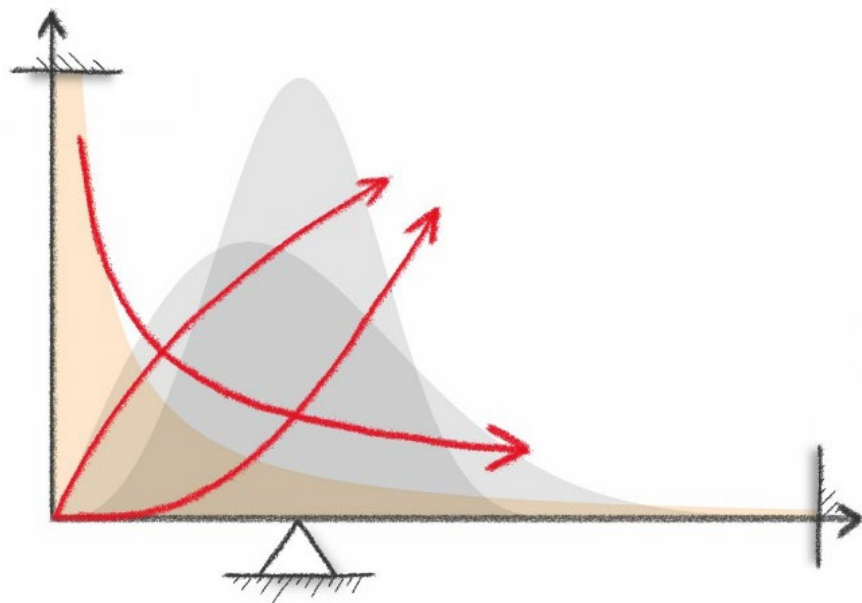
This approach of selectively using 'favourable' data yields absurd **failure rate** and **MTBF** estimates. Another issue is the concept of '**environmental factors**' as illustrated in the table below.

Section #		Part Type or Dielectric		Generic Failure Rate, $\lambda_g$ (Failures/10 <sup>6</sup> Hours) for Capacitors																
				$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$	$\lambda_g$		
		Style	MIL-C	Env. = 40 °C	40	45	40	45	55	70	70	80	80	100	100	100	100	100	100	100
				$T_A$ (°C) = 30	40	45	40	45	55	70	70	80	80	100	100	100	100	100	100	100
10.1	Paper, Dry-Proof	CP	25	.0026	.0072	.001	.018	.055	.025	.03	.010	.13	.080	.0018	.044	.12	2.1			
10.1	Paper, Dry-Proof	CA	11800	.0039	.0087	.041	.022	.070	.035	.047	.19	.35	.13	.002	.056	.18	8.5			
10.2	Paper/Plastic, Fast Through	CPL	1100	.0047	.0098	.044	.034	.079	.030	.040	.094	.15	.11	.0024	.058	.18	2.7			
10.3	Paper/Plastic Film	CPW	11147	.0021	.0042	.017	.010	.030	.0088	.013	.026	.048	.044	.0010	.023	.063	1.1			
10.3	Paper/Plastic Film	COR	10979	.0021	.0042	.017	.010	.030	.0088	.013	.026	.048	.044	.0010	.023	.063	1.1			
10.4	Metallized Paper/Plastic	CH	13022	.0029	.0058	.023	.014	.041	.012	.018	.037	.066	.060	.0014	.033	.088	1.5			
10.4	Metallized Plastic/Film	CH	13212	.0029	.0058	.023	.014	.041	.012	.018	.037	.066	.060	.0014	.033	.088	1.5			
10.5	Metallized Paper/Plastic	CPL	15514	.0041	.0083	.042	.021	.067	.026	.048	.086	.14	.10	.0020	.054	.15	2.5			
10.6	Metallized Plastic	CH	18141	.0023	.0042	.018	.012	.033	.0096	.014	.024	.052	.048	.0011	.026	.07	1.2			
10.7	MICA (Dipped or Mounted)	CA	3001	.0005	.0015	.0001	.0044	.014	.0068	.0095	.054	.080	.031	.00025	.012	.046	.45			
10.7	MICA (Dipped)	CA	3001	.0005	.0015	.0001	.0044	.014	.0068	.0095	.054	.080	.031	.00025	.012	.046	.45			
10.8	MICA (Butter)	CH	13063	.018	.037	.18	.094	.31	.10	.14	.47	.80	.46	.0061	.25	6.8	11			
10.9	Glass	CPL	2700	.00032	.00096	.0059	.0028	.0094	.0044	.0062	.035	.045	.030	.00016	.0076	.030	.38			
10.9	Glass	CT	11272	.00032	.00096	.0059	.0028	.0094	.0044	.0062	.035	.045	.030	.00016	.0076	.030	.38			
10.10	Ceramic (Gen. Purpose)	CP	11015	.0036	.0074	.034	.019	.056	.015	.015	.032	.048	.077	.0014	.040	.13	2.3			
10.10	Ceramic (Gen. Purpose)	CP	11015	.0036	.0074	.034	.019	.056	.015	.015	.032	.048	.077	.0014	.040	.13	2.3			
10.11	Ceramic (Temp. Comp.)	CPL	20	.00078	.0022	.013	.0056	.028	.0077	.015	.050	.12	.046	.00026	.017	.065	.88			
10.11	Ceramic Chip	COR	10981	.00078	.0022	.013	.0056	.028	.0077	.015	.050	.12	.046	.00026	.017	.065	.88			
10.12	Tantalum, Solid	CPL	1000	.0018	.0039	.015	.0097	.028	.0091	.011	.024	.057	.065	.00072	.022	.068	1.0			
10.13	Tantalum, Non-Solid	CL	1000	.0061	.013	.061	.038	.11	.021	.061	.13	.29	.18	.0050	.080	.26	4.0			
10.13	Tantalum, Non-Solid	CL	1005	.0061	.013	.061	.038	.11	.021	.061	.13	.29	.18	.0050	.080	.26	4.0			
10.14	Aluminum Oxide	CA	30114	.024	.061	.42	.18	.58	.46	.55	2.1	2.6	1.2	.012	.49	1.7	21			
10.15	Aluminum Dry	CE	62	.029	.081	.58	.24	.83	.73	.88	4.3	5.4	2.0	.015	.68	2.8	29			
10.16	Variable Plastic	CT	81	.08	.27	1.2	.71	2.3	.89	1.1	6.2	12	4.1	.032	1.9	5.9	85			
10.17	Variable, Plastic	PC	1400	.030	.15	.82	.31	.93	.21	.28	2.2	3.3	2.2	.018	.89	3.2	37			
10.18	Variable, Air-Terminal	CD	2010	.080	.33	1.8	.87	3.0	1.0	1.7	8.8	18	8.1	.033	2.5	8.9	100			
10.19	Variable, Vacuum	CD	2010	0.4	1.5	8.7	3.8	13	5.7	10	58	90	39	.20	1	1	100			
10.19	Variable, Vacuum	CD	2010	0.4	1.5	8.7	3.8	13	5.7	10	58	90	39	.20	1	1	100			



This table is also from **MIL-HDBK 217F**, with each column containing a factor that engineers are intended to apply to **baseline failure rates**. Environmental conditions such as 'benign,' 'extreme,' 'humid' and other military-specific environments are included. However, the source of these factors is not revealed, nor (in light of the other inaccuracies described above) can they be reasonably assumed as accurate.

Perhaps the most egregious issue with **generic reliability tables** is that they all assume a **constant hazard rate**, which implies that products never age, **wear out** or **wear in**. The **MTBF** is simply the balance point of the **probability density curves** that describe the **time-to-failure** of different components. All curves below have different shapes, but all share the same **MTBF** or balance point.



The red lines represent the different **hazard** or **failure rates** for each **probability density curve**. They too all have the same **average**. Being provided a single number that characterizes the **failure rate** (and **MTBF**) only doesn't describe if the component is **wearing in**, **wearing out**, or doing anything else.

The data used to generate these numbers is often decades old and somewhat limited as companies tend to never divulge their **reliability** (or **failure**) data. Notwithstanding, seemingly precise numbers can create a false sense of accuracy. For example, a **failure rate** of **1.2967 failures per million hours** seems precise but could be based on a single **failure** data point.

Generic **reliability** tables don't take into consideration different manufacturing qualities from different suppliers, how operators maintain components, or anything else that adds to the uniqueness of different types of components.

**Generic reliability tables** can also be very 'tempting' to use. They provide traceable, referenceable numbers. Simply copying numbers from a **generic table** can also be used to replace testing and analysis. And once these generic numbers enter tables and reports, they tend to never be challenged throughout product development.

## ... using generic RELIABILITY TABLES and PARTS COUNT PREDICTION

There is nothing wrong with **generic reliability tables**. There is, however, plenty wrong with using those numbers blindly without question. **Generic reliability tables** can be used to help compare indicative types of subsystems. For example, some of the elements of the milling machine described above could be entirely mechanical, electro-mechanical, or computer numerically controlled (CNC). Each subsystem has its own set of pros and cons, and understanding the likely **reliability** characteristics of each is part of that.

However, using **generic reliability tables** to characterize **failure** and sparing behavior always leads to widely inaccurate results. There is a tendency for numbers that enter preliminary reliability reports to never be challenged, meaning that companies might genuinely believe their capacitors will last over 30 000 years.