

Reliability, Availability and Maintainability (RAM) Practitioners Course

If reliability engineering isn't making you money, then you are doing it wrong



Workbook

Presented by

Dr Chris Jackson

Reliability engineer



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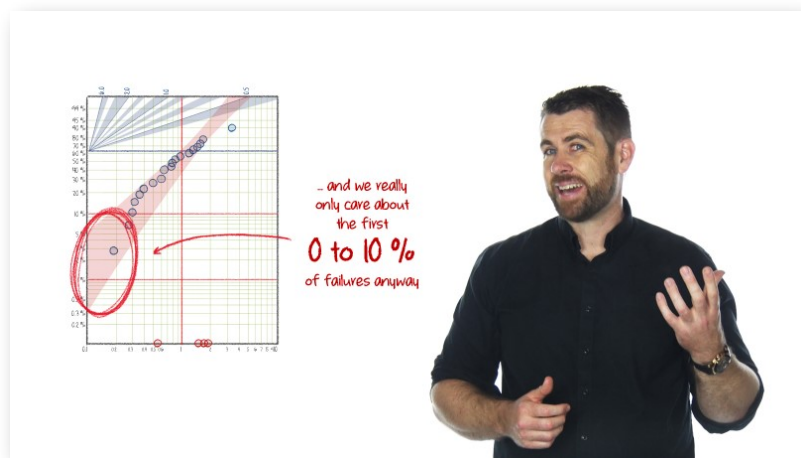
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Who is your teacher? ... Dr Chris Jackson

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 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.

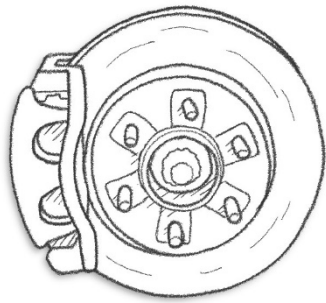
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Reliability life models

Not many people associate automobile brake pad wear with reliability. Brake pads are supposed to wear out. We know this. Which is why we don't really look at a brake pad as if it has 'failed' when it wears out.

But the approach to understanding how long it takes for a brake pad to wear out, its current state of wear, and when we should schedule brake pad replacement is basic reliability engineering.

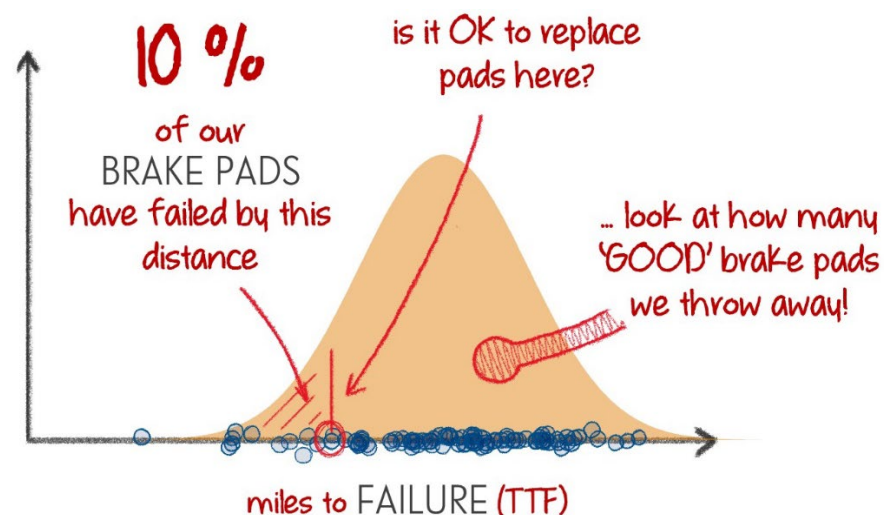


Brake pads convert kinetic energy to thermal energy when the calipers clamp them to the spinning rotor. This slows our vehicle down.

This energy conversion eventually wears the brake pad material away. We actually have a pretty good idea of how fast this occurs when we have a good idea of the amount of energy involved.

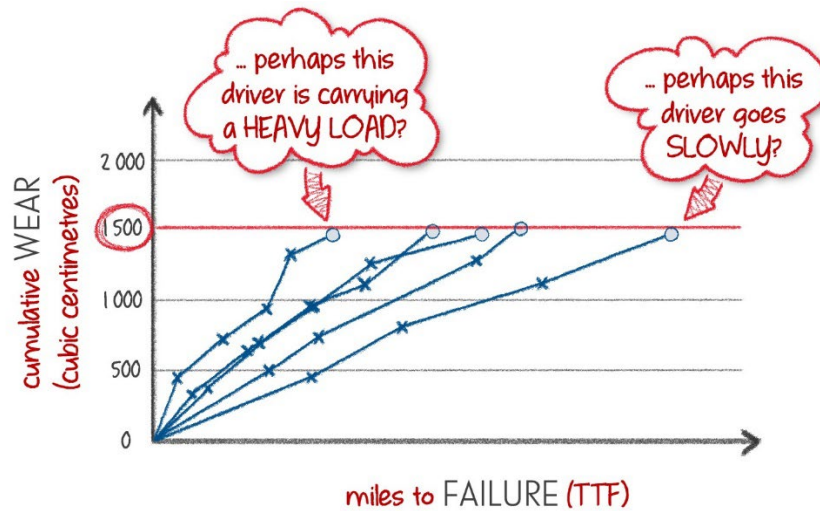
But the problem for most vehicles is that the only usage metric we often track is distance travelled. This involves a lot of uncertainty that includes different driving behaviors, typical speeds, amount of highway versus urban driving, vehicle (and load) mass and so on. So trying to estimate how long we should wait to replace our brake pads based on distance is a little uncertain because we don't know how much energy needs to be 'lost' through braking.

This uncertainty usually forces us to be conservative. And by that we mean risking throwing out 'good' brake pads as opposed to risking NOT throwing out 'bad' brake pads.

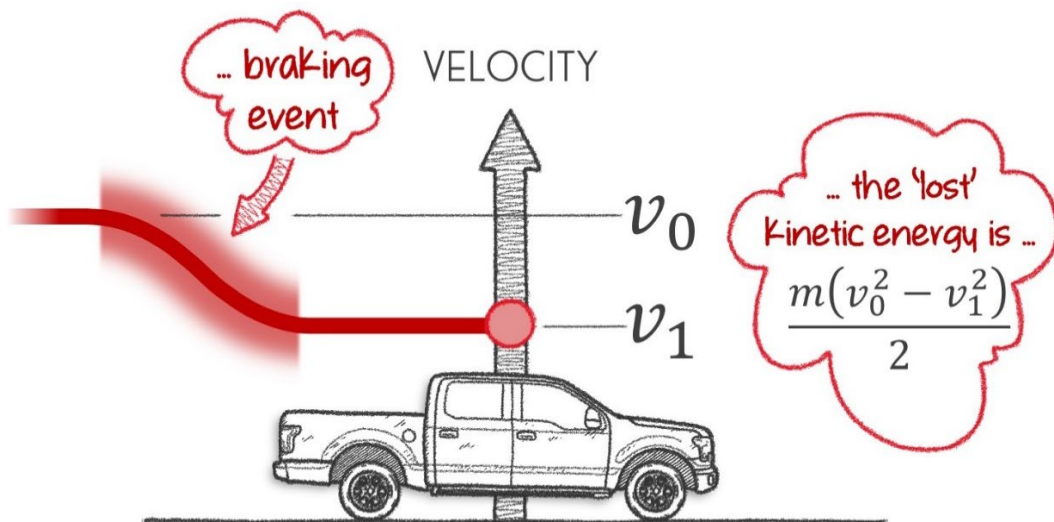


So if we can somehow understand the rate of brake pad wear better, we can save a lot of time and money. And perhaps we can reward drivers who drive more carefully!

The problem starts with the fact that distance is not a particularly good usage metric. The following chart illustrates just how different brake pad wear can be for different vehicles, with different drivers and different loads.

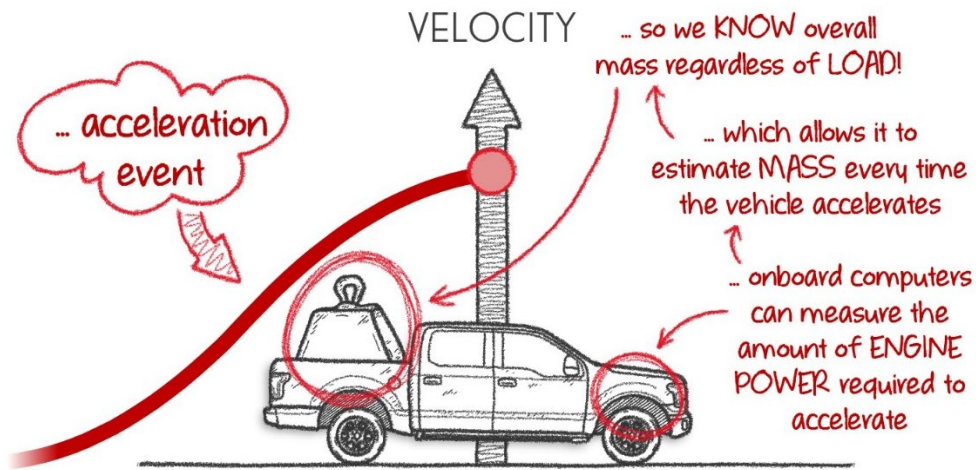


This is where our understanding of the wear mechanism (or any other failure mechanism) becomes incredibly useful. We know that the amount of brake pad material that is worn away is proportional to the amount of kinetic energy that is transferred to thermal energy. And all we need to know for each braking event is the start and finish velocities, along with the mass of the vehicle (with any load).



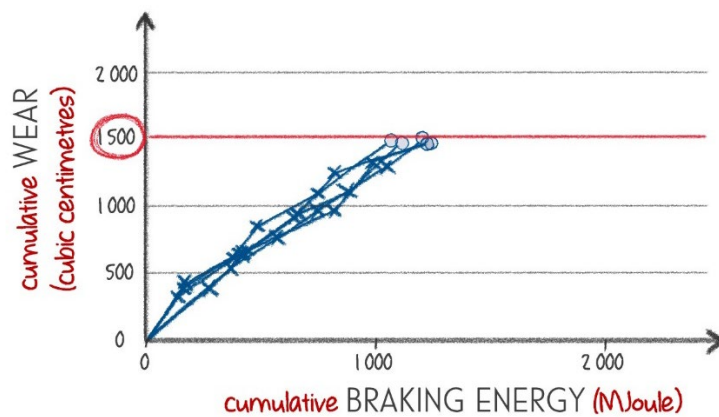
Vehicles are getting smarter and smarter these days. On board computers can measure the initial and final speeds of each braking event. But the vehicle mass ... with any load?

Ford Motor Company solved this problem! And it has everything to do with acceleration events.

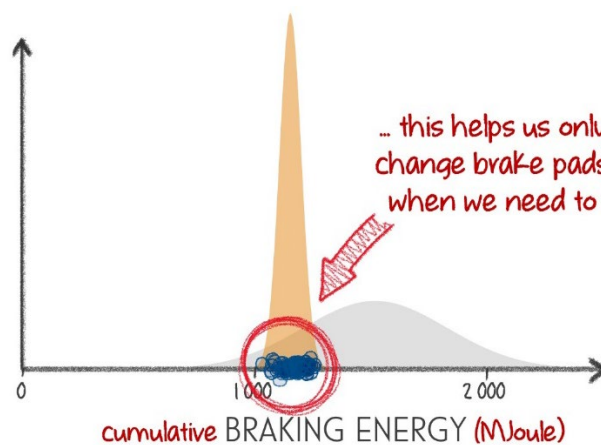


Ford vehicles are able to constantly estimate vehicle (and load) mass every time the driver presses the accelerator. So even if it is loaded, unloaded, takes on passengers and so on, the on-board computer has a really good understanding of vehicle (and load) mass ... all the time.

And look at what this does to actual brake pad wear ... when we stop measuring usage in terms of miles and replace it with cumulative braking energy.



Which means we are now much more certain about if and when we need to replace brake pads!

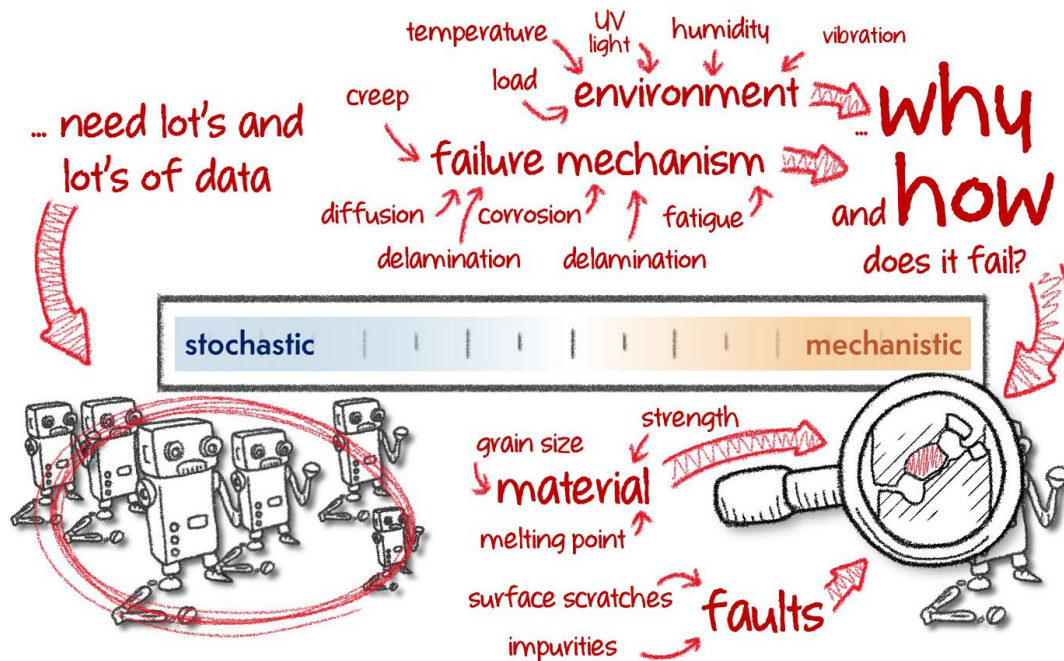


... the CONTINUUM OF RELIABILITY LIFE MODELS

Some of us no doubt think that creating complex models of **failure** that take into consideration temperature, vibration profiles, yield strain, humidity and lots of other factors ... is horrible. This can be true. But as the brake pad example showed above, sometimes all we need is a basic understanding of the underlying **Physics of Failure (PoF)** to help us make that decision that we have been otherwise stressing over.

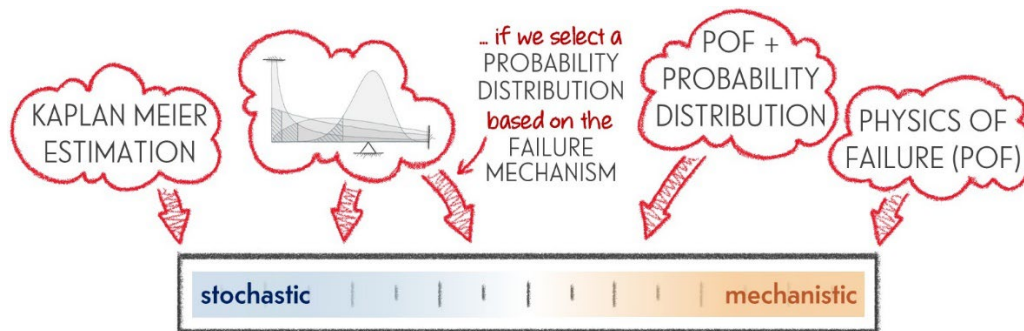
We call **PoF models 'mechanistic'** as we focus on trying to understand the **failure mechanism** that drives **failure**. Some **mechanistic models** can indeed be complex, with all sorts of different environmental parameters potentially coming into play. The reason **mechanistic models** can be so useful is that simply understanding the mechanism represents information. Information that you don't otherwise have to generate through testing, field data or (worst of all) customer feedback.

'**Stochastic models**' are the opposite of '**mechanistic models**.' **Stochastic models** are all about finding a 'good enough' **probability distribution**. Because we aren't bringing in lot's of information through an understanding of the **PoF**, we often need lots (and lots and lots) of data



And of course, there are lots variations between the two extremes. We know there are lots of **probability distributions** and in many cases talked about the nature of **failure**. So when we can combine a **stochastic model** with at least some understanding of the **PoF** to incorporate more information. Which saves us from having to gather more data.

Some different families of **reliability life models** are shown below, along with their position on the **reliability life model continuum**.



Kaplan Meier estimation is 'purely' stochastic in that it doesn't involve any models at all. It requires an EXTRAORDINARY amount of information to generate information to help make better decisions (and won't be covered in this lesson).

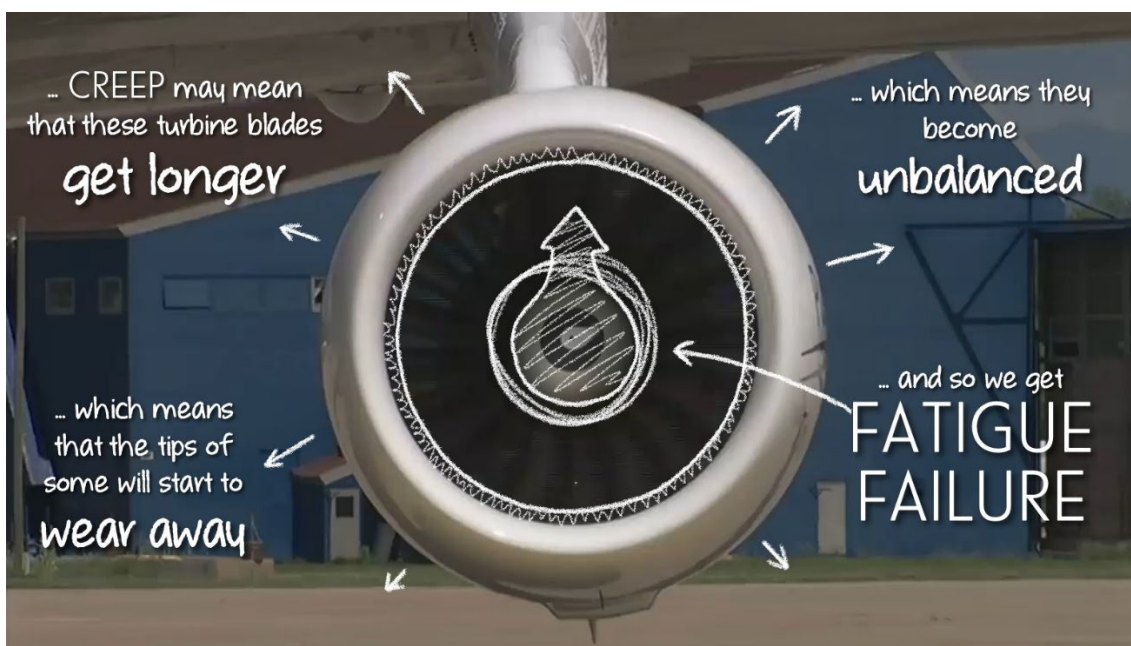
We can also see the **probability distributions** above, but because they are models that involve at least some additional information. We incorporate even more information if we select the **probability distribution** based on our knowledge of the **failure mechanism**.

On the right, we have our **PoF models**, and **PoF models that involve a probability distribution**. And we start by looking at these models first.

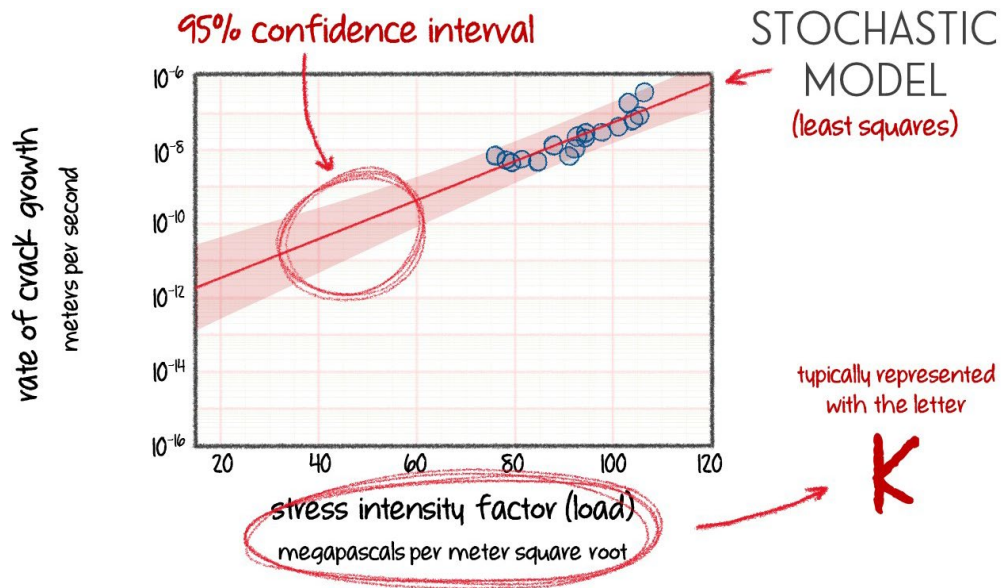
... let's look at a MECHANISTIC MODEL

CREEP is the tendency of a solid material to deform permanently under the influence of mechanical stresses.

We often forget about creep ... as it is not as 'popular' as **failure mechanisms** like fatigue and corrosion.

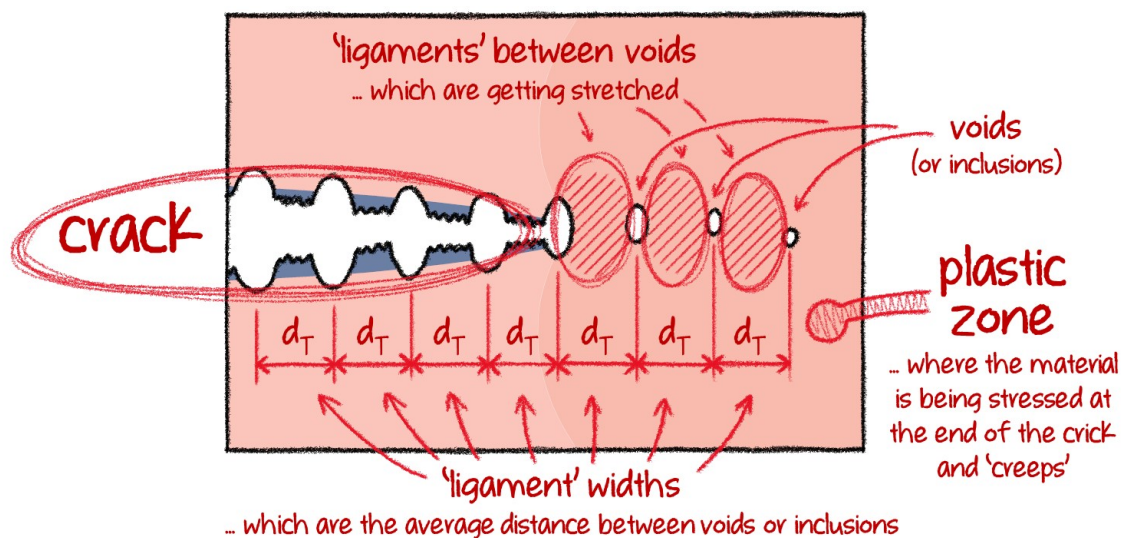


So let's say we are interested or concerned about creep in AISI 4340 steel. Perhaps we will conduct some testing and get data that is plotted in the chart below. ¹



A basic **stochastic model** has been applied (with **confidence bounds**). It essentially revolves around an assumption that the **logarithm** of the rate of crack growth is proportional to the stress intensity factor.

So let's try and incorporate a **mechanistic model**, like the Tensile Ligament Instability (TLI) model that is really useful for creep crack growth in brittle materials.



... there are some complicated equations on the next page ...
but don't worry – they are only to illustrate a concept!

¹ Landes, J.D., and Wei, R.P. Comparison of a Mechanistically based probability model and a statistical model for the steady-state creep growth rate, Journal of Engineering Materials, and Technology, Transactions of the ASME, Vol. 95, 1973 pp.2-9

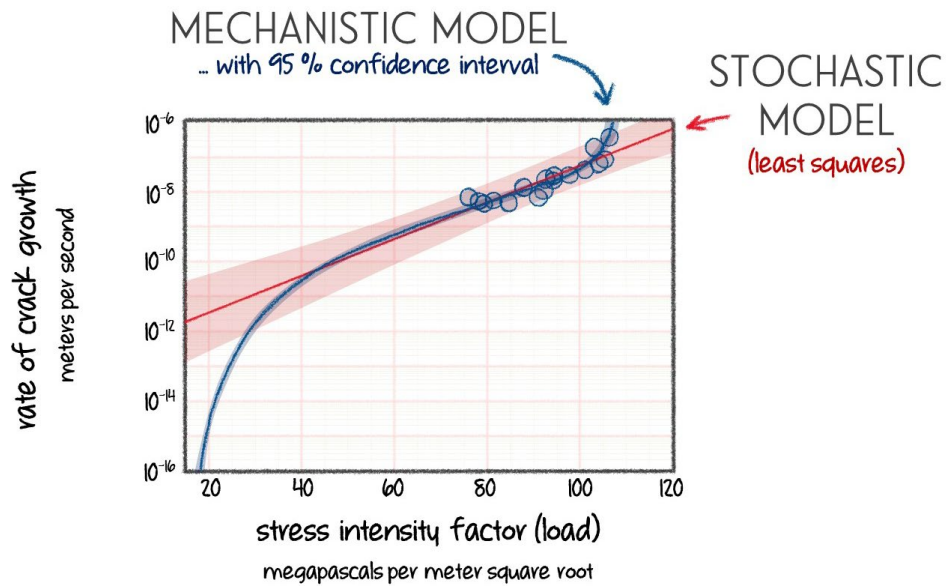
The TLI model is of itself incomplete. It needs three additional models to be embedded 'in it' to create the following monstrosity of an equation ... ^{2, 3, 4, 5, 6, 7}

$$\frac{da}{dt_{ss}} = \frac{1}{n} \cdot \frac{(1+n)d_T}{1 - \left(\frac{K}{K_C}\right)^{\frac{1+n}{2}}} \cdot \frac{d\varepsilon}{dt_{ss}}$$

$d_T = \left(\frac{K_C}{\sigma_{YS}\sqrt{\pi}}\right)^2 \left(\frac{3\varepsilon_{YS}}{4n}\right)^{1+n}$
 $\frac{d\varepsilon}{dt_{ss}} = A \left(\frac{\sigma - \sigma_0}{G}\right)^M$
 $K = \sigma_{YS}\sqrt{\pi} \left(\frac{\sigma \cdot d_T^{1+n}}{1.2\sigma_{YS}}\right)^{\frac{1+n}{2}}$

Annotations:
 - $\frac{da}{dt_{ss}}$: speed of crack growth
 - n : strain hardening exponent
 - $(1+n)$: yield strain
 - d_T : yield stress
 - K_C : plane stress fracture toughness
 - $\frac{d\varepsilon}{dt_{ss}}$: creep rate coefficient
 - M : creep rate exponent
 - A : hardness
 - G : shear modulus
 - $\frac{1+n}{2}$: ... and the 'SS' represents 'steady state'
 - K : plane stress fracture toughness

And when we combine this **mechanistic model** with the observed data we get ...



² Landes, J.D., and Wei, R.P. Comparison of a Mechanistically based probability model and a statistical model for the steady-state creep growth rate, Journal of Engineering Materials, and Technology, Transactions of the ASME, Vol. 95, 1973 pp.2-9

³ Yin, J., Gao, M., and Wei, R.P., Deformation and Subcritical Crack Growth Under Static Loading, Materials Science and Engineering, Vol. A119, 1989, pp. 51-58

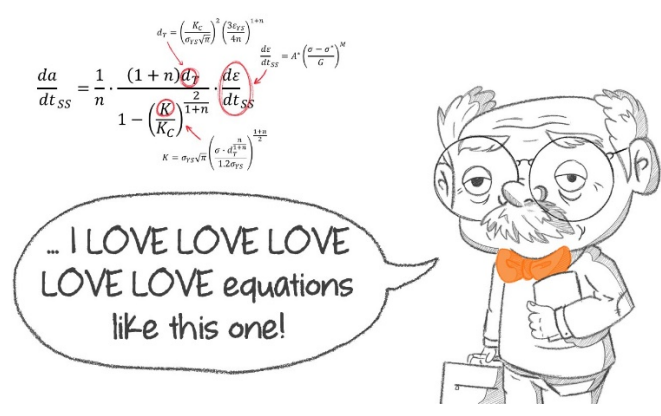
⁴ Hart, E.W., "A phenomenological Theory for Plastic Deformation in Polycrystalline Metals," Acta Metallurgica, Vol 18, 1970, pp.599-610

⁵ Hart, E.W., "Constitutive Relations for the Nonelastic Deformation of Metals," Journal of Engineering, Materials, and Technology, Transactions of the ASME, Series H, Vol. 98, No. 3, 1976, pp.193-202

⁶ Hart, E.W., Li, C.Y., Yamada, H., and Wire, G.L. "Phenomenological Theory: A Guide to Constitutive Relations and Fundamental Deformation Properties," Constitutive Equations in Plasticity, A.S. Argon, Ed., MIT Press, Cambridge, MA 1975, pp. 149-197

⁷ Hilton, P.D., and Hutchinson, J.W. Engineering Fracture Mechanics 3, 1971, pp. 435-451

Yin, H., Gao, M., and Wei, R.P., Corrosion 52, 1996, pp. 8-15



... but no one else does ...

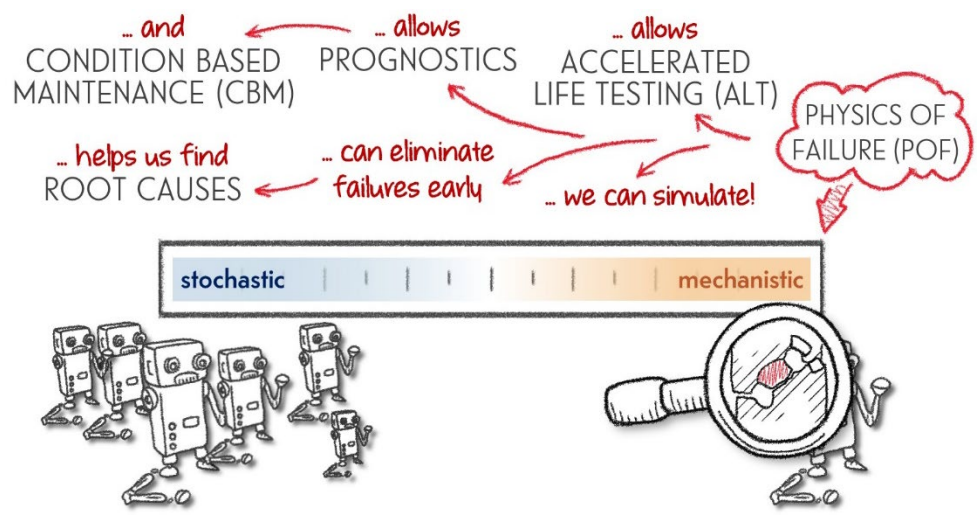
We should do a lot of other things before we think about using this **equation** to help us understand **reliability**. This starts with identifying the VITAL FEW ways your product, system or service will **fail** using activities like **FMEAs** and **HALT**. If the component that is subject to creep is not one of the VITAL FEW ... then don't worry about this equation! Engineering judgment may suffice.

But let's just say the component that might just **fail** due to creep makes the VITAL FEW ... then what do we do? Still don't be afraid! If we are able to get the **equation** on the previous page that describes creep crack growth, we can see that we have eight different material properties that are relevant:

$$K_C, A^*, \sigma_{YS}, \sigma^*, \epsilon_{YS}, G, n, M$$

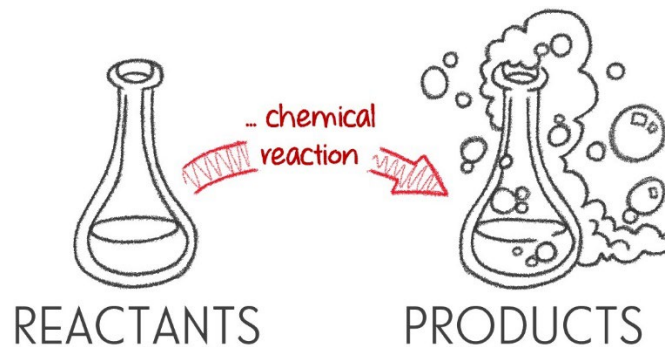
We can work out which ones matter the most, and then make sure we select steel based on these parameters. This can simply help us work out which steel is better ... even if we don't use the **equation** to **model reliability**.

And **PoF models** help us do lots of other really useful things as well.



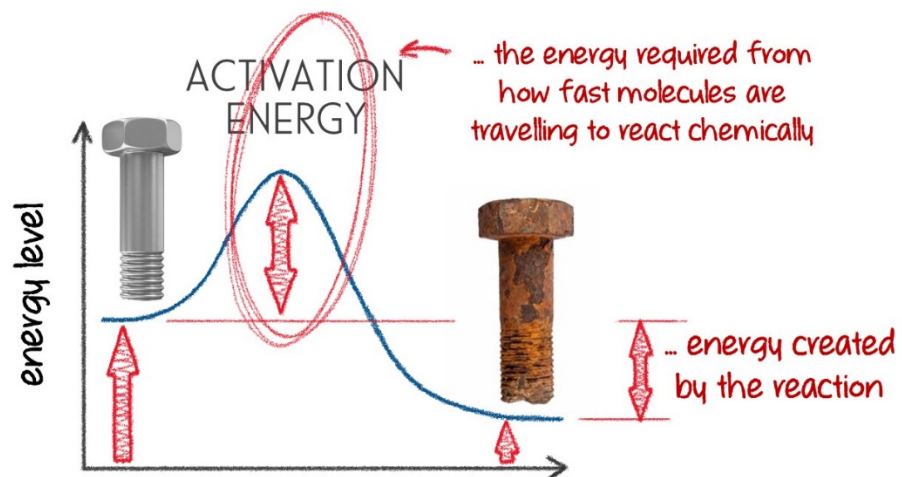
... so what is ACCELERATED LIFE TESTING (ALT)

Let's start with looking at **failure mechanisms** that are based on chemical reactions. There are lots of them out there. Corrosion, diffusion, and lots of others. So what happens in a chemical reaction?



... reactants *WANT* to become *PRODUCTS* ...

Why is this? Because products exist in a lower energy state. And states of lower energy is where everyone and everything wants to go. Just like a ball 'wants' to roll down a hill. But when it comes to chemical reactions, there is a little barrier for the reactant when it is at the top of this hill.



So to speed up the reaction, we need to give more and more energy to the reactant. And one way of doing this is to increase the temperature of the reactants which makes the molecules travel faster. Which means they have more energy.

There is a well-known model (**Arrhenius model**) that relates the increased temperature to rate of chemical reaction.

ACTIVATION ENERGY

$$k = A e^{-\frac{E_a}{kT}}$$

... the rate of the reaction (which is the frequency of collisions that have enough energy to cause the chemical reaction) → k
 ... constant for each chemical reaction → A
 ... Boltzmann's constant $1.3806504 \times 10^{-23}$ Joules per Kelvin → k
 temperature in degrees Kelvin → T

We can rearrange this equation to get ...

$$\frac{c}{L} = A e^{-\frac{E_a}{kT}}$$

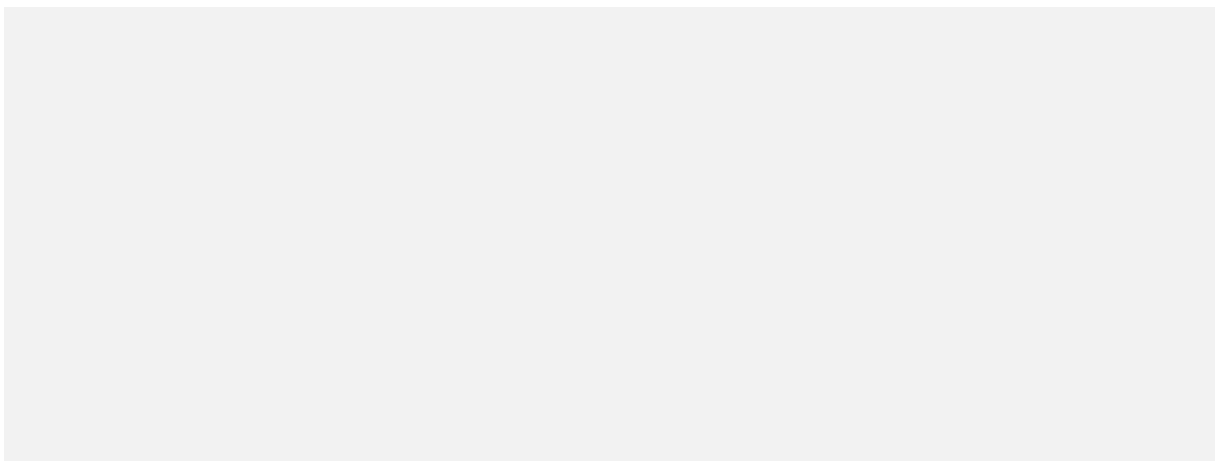
... some constant → c
 ... the CHARACTERISTIC LIFE → L

And we can rearrange it further to get ...

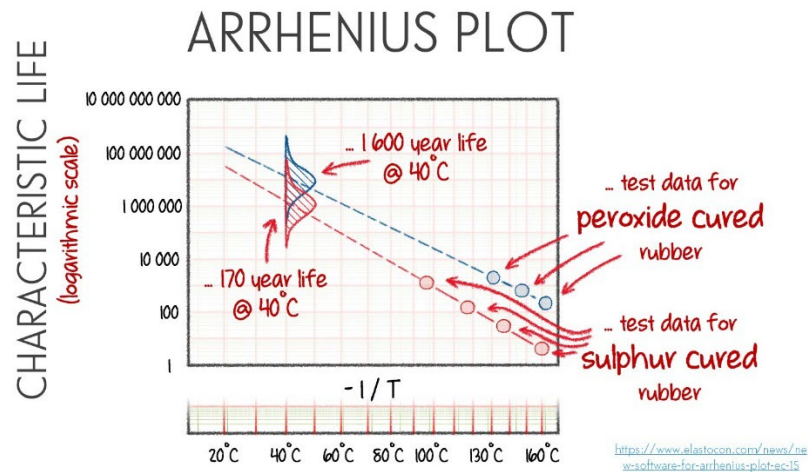
$$\ln L = \ln c - \ln A + \frac{E_a}{k} \left(\frac{1}{T} \right)$$

... the reason we did this was because we can now create a **straight line**
 (... even if this is not obvious right now)

We can take this equation to create a special graph, called an **Arrhenius Plot** (illustrated on the next page).

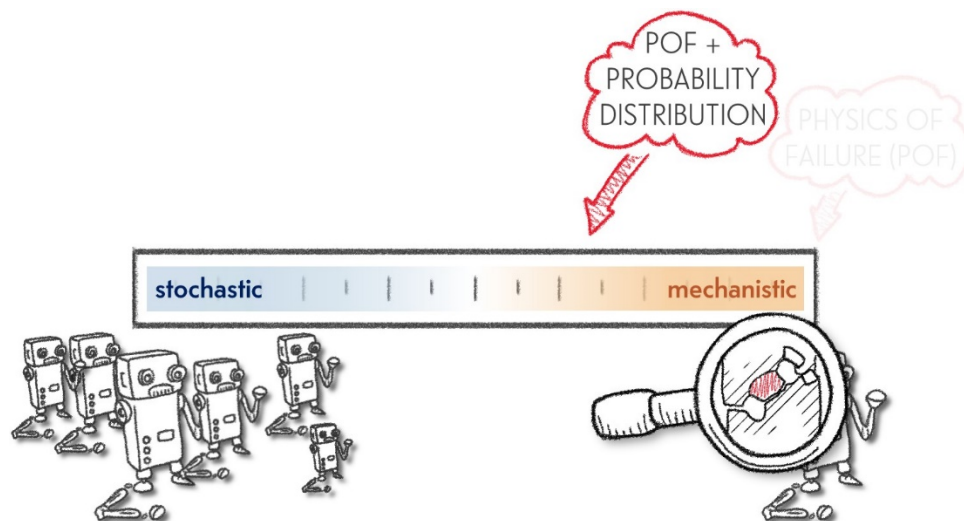


In this example, we can expose different rubbers to higher temperatures to see how long it takes for them to **fail**. We can then use this data to predict how long they will last in actual use conditions. This means we can accelerate 'degradation' by factors (in this case) of 10 000. So testing is fast and meaningful.



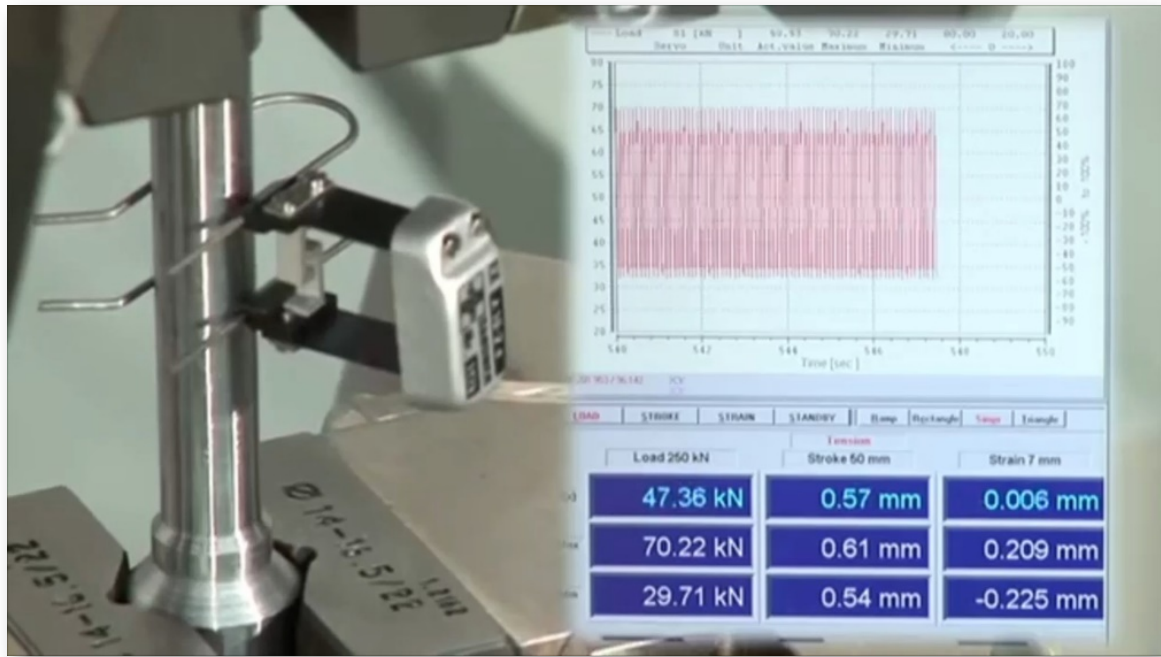
The data on the bottom right-hand corner of the chart doesn't take very long to gather as the temperature has been increased. We can see that because the data creates a straight line, the **Arrhenius model** appears to be a good fit.

We also know that because chemical reactions are typically constant, the **normal distribution** should model any randomness in the **TTF**. So here is an example of using the **Arrhenius model** to incorporate our understanding of the **PoF** and combine it with a 'stochastic' or 'random' model in the form of a **normal probability distribution**.

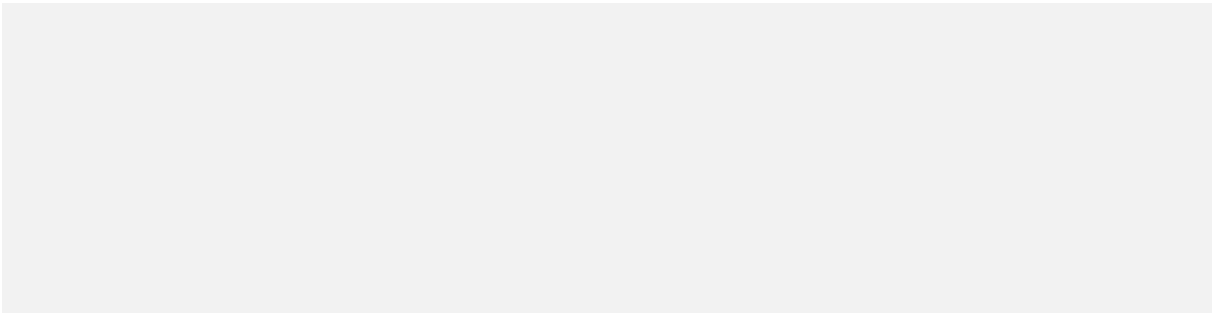
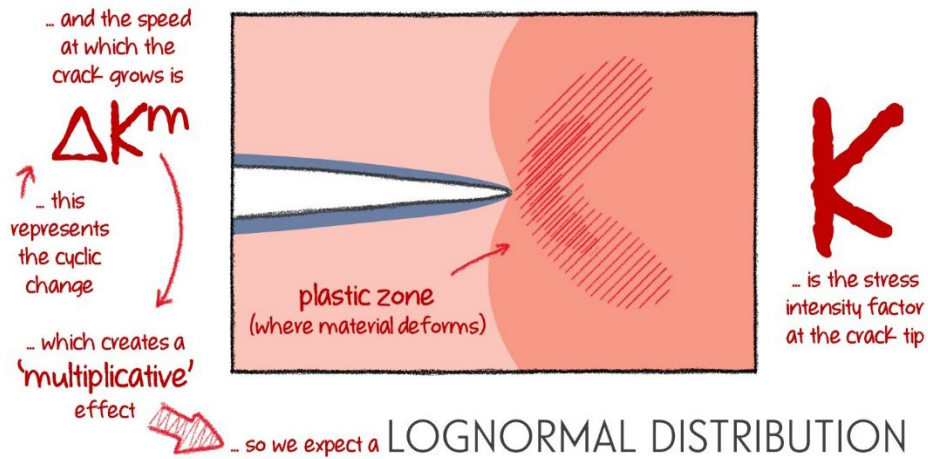


... but sometimes we DO HAVE DATA

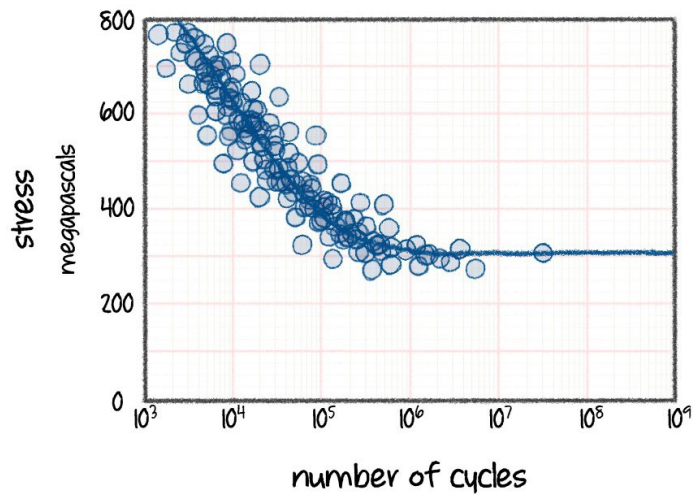
Let's look at fatigue, where cyclic stresses lead to crack growth. Most steels have been subjected to thousands of fatigue tests in materials laboratories across the world. So this is one of the few cases where we have a LOT of data.



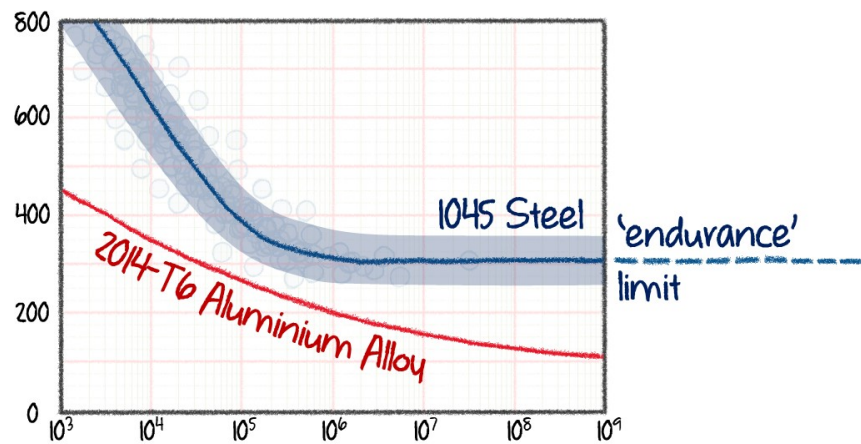
So what is happening at tip of a fatigue crack?



So what happens when we get all this fatigue data?



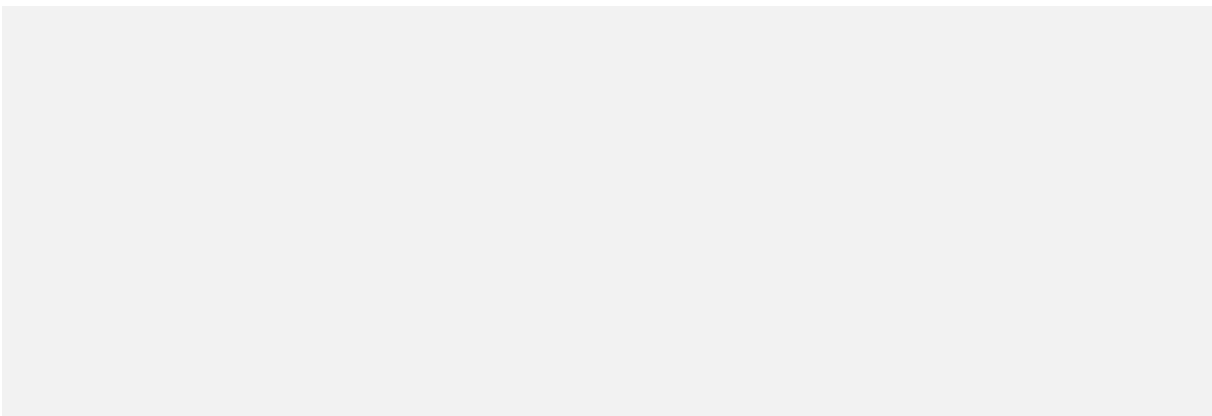
And eventually we get enough points to create the following chart ...



These are examples of **non-parametric models**.

*a NON-PARAMETRIC MODEL is a random model
without a probability distribution*

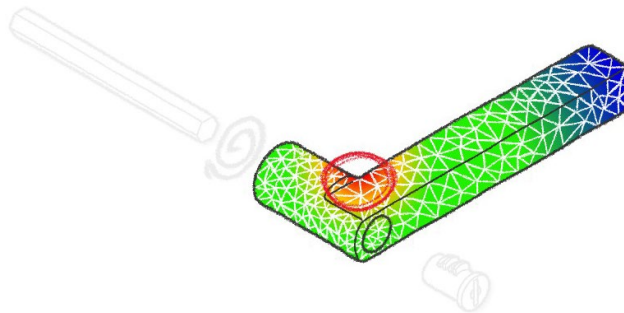
But even then, we can use a **probability distribution** (like we did in [the lognormal distribution lesson](#)) to do an even better job of modelling reliability.



... BONUS! ... how to use the lognormal distribution for fatigue

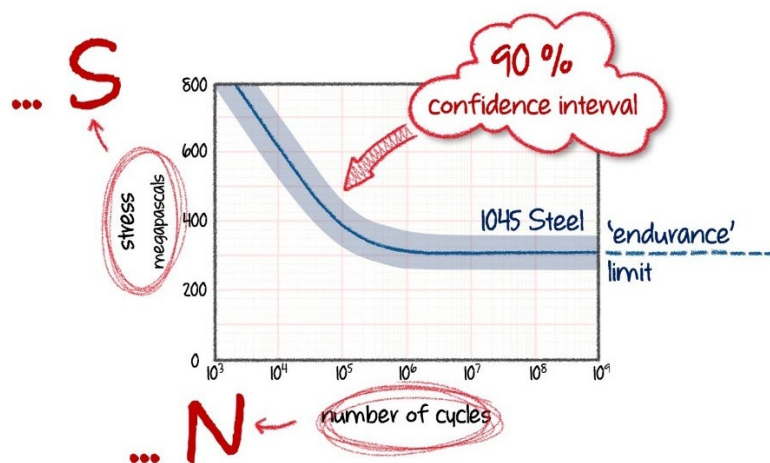
Let's look at the handle of a smart lock. We are planning on manufacturing it out of 1045 steel, which can be prone to fatigue failure. The door handle will routinely be opened and shut, so there will be a cyclic stress applied to it.

We conduct **Finite Element Analysis (FEA)** on the preliminary design and identify a region of stress concentration on the inside of the handle. And the local stress the handle will experience when the handle is opened with a 'high' level of force is 500 MPa. This will be used at the (conservatively high) assumed stress for each door handle use.



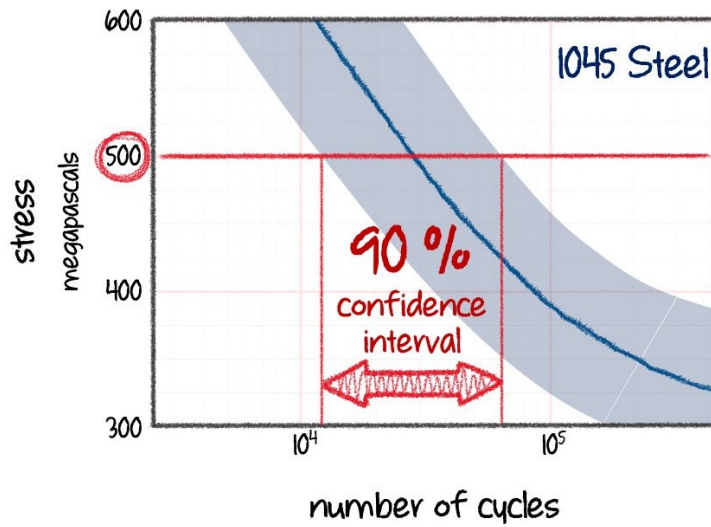
We know (from experience) that the **lognormal distribution** does a good job of modelling fatigue failure. As a fatigue crack grows bigger, it concentrates more stress at the crack tip. So the crack grows faster in a 'multiplicative' way.

We can obtain what we call an 'S-N' chart for 1045 steel which describes its fatigue characteristics.

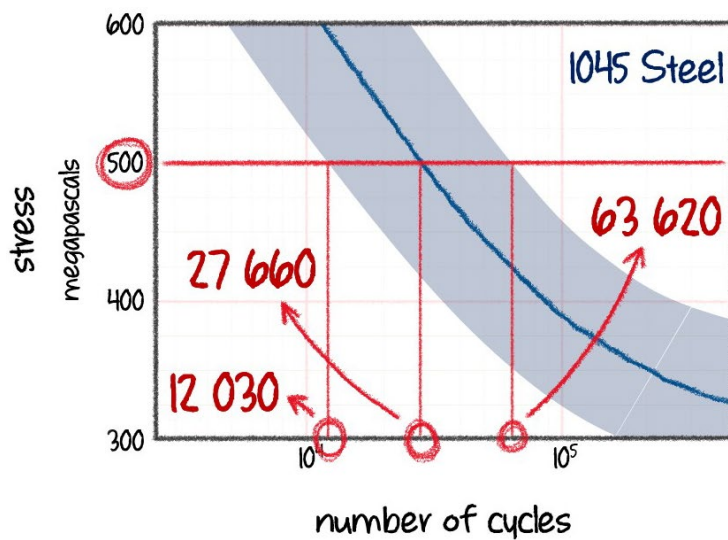


You can see that the horizontal scale of the 'S-N' chart above is **logarithmic**. And because fatigue cycles to failure is described by the **lognormal distribution**, the *logarithm* of fatigue cycles to failure should be described by the **normal distribution**.

Now let's zoom in on 500 MPa. And this allows us to identify the 90 % **confidence interval** of cycles to failure - within which we expect our 1045 steel to **fail** due to fatigue.

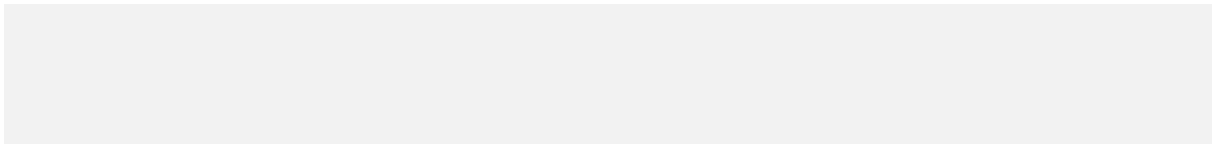


We can identify the boundaries and mid point of this interval using this chart.

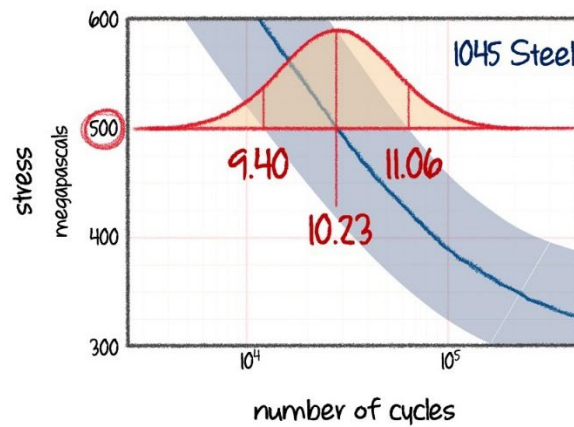


What we are going to do now is use the **normal distribution** (noting that this chart uses a **logarithmic scale**). So we can't use the cycle numbers above - we need to use the **logarithms** of these numbers

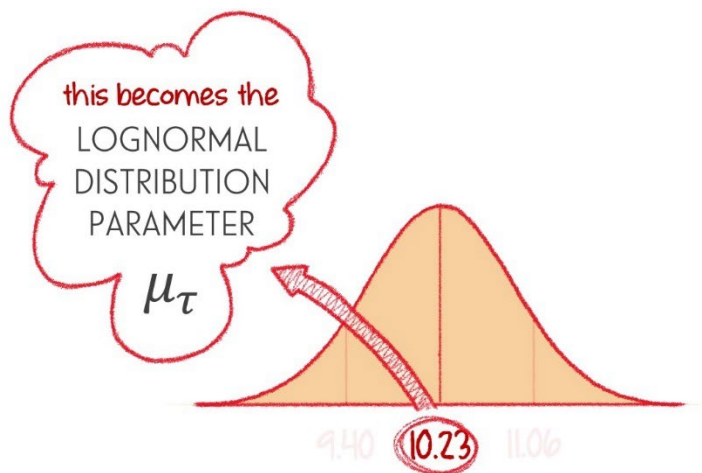
	NATURAL LOGARITHM - ln
12 030	9.40
27 660	10.23
63 620	11.06



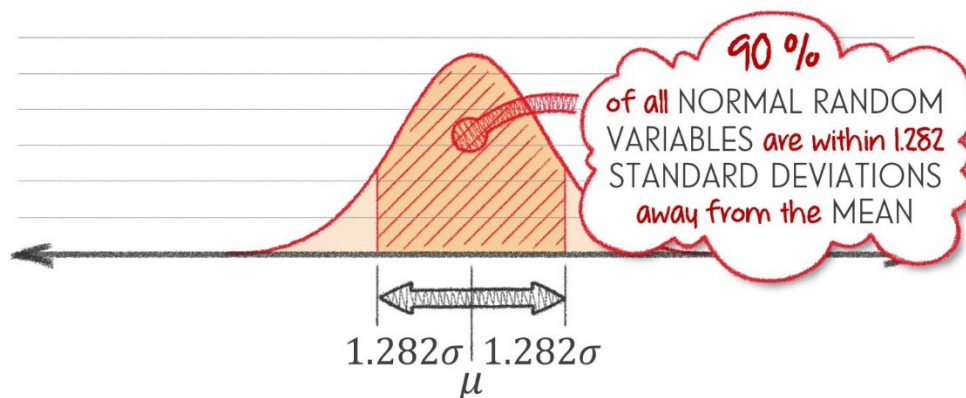
So let's superimpose a bell curve (**normal distribution**) over our **confidence interval**.



So the middle of this superimposed **normal distribution PDF curve** gives us the first parameter of our **lognormal distribution**.

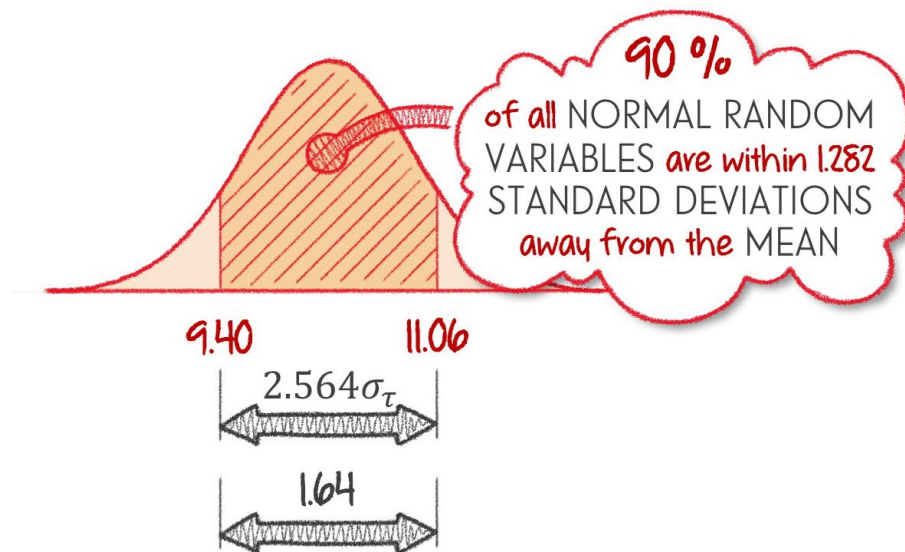


Now a characteristic of the normal distributions if we are interested in the 'middle' 90 % of **normally distributed random variables** ...



This means that the 90 % **confidence bounds** are each 1.282 **standard deviations** from the **mean**.

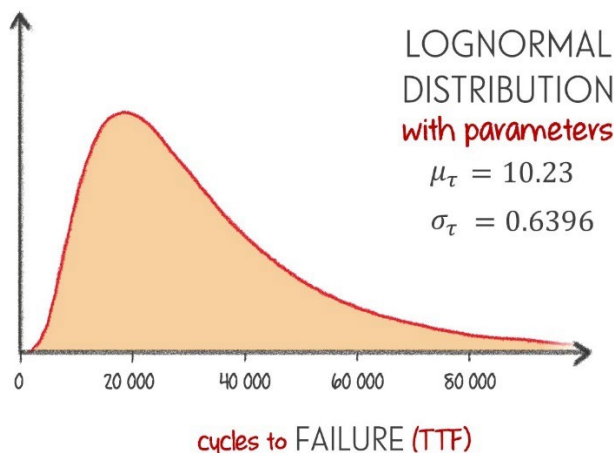
For our **normal distribution PDF curve** superimposed onto the 90 % **confidence interval** ...



This allows us to calculate the second **lognormal distribution** parameter, σ_τ ...

$$\sigma_\tau = \frac{1.64}{2.564} = 0.6396$$

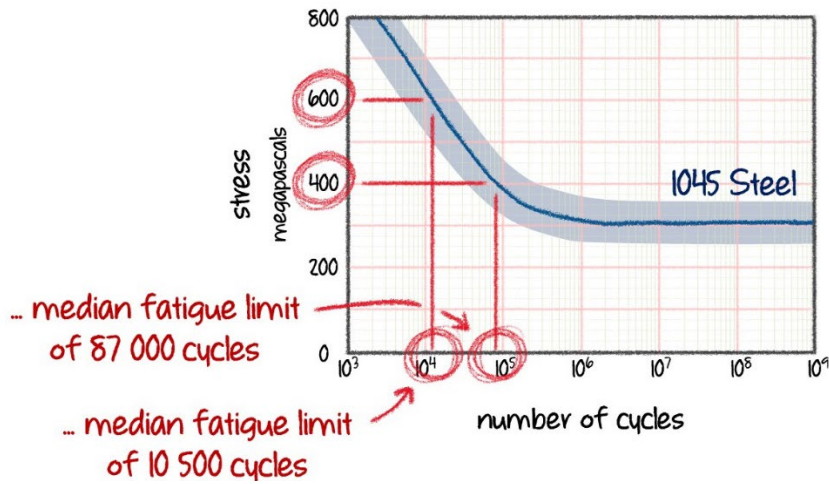
This allows us to model the cycles to failure for our door handle if it is based on fatigue as follows ...



... then there are **DAMAGE MODELS**

There are things called **damage models** that attempt to model how parts and components accumulate damage when they are exposed to different stresses.

Let's say we have a 1045 steel strut that is routinely subjected to different stress levels – 400 and 600 MPa. The **median fatigue limits** are 87 000 and 10 500 cycles respectively.



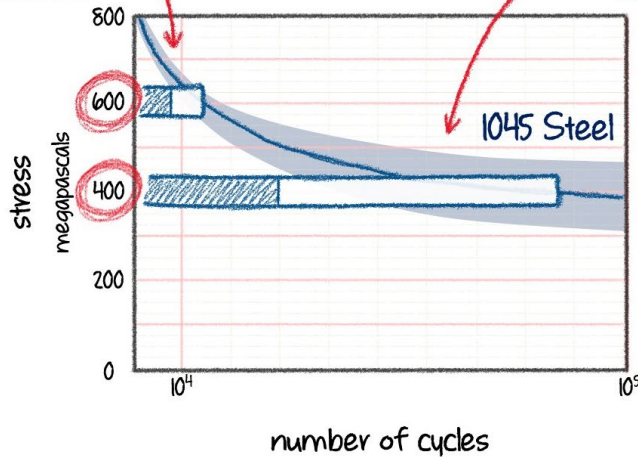
Remember, the horizontal axis above is in a **logarithmic scale**. So let's say our strut is exposed to 7 500 cycles at 600 MPa and 30 000 cycles at 400 MPa

... 7 500 cycles @ 600 MPa takes up

50 %
of the bar

... 30 000 cycles @ 400 MPa takes up

34 %
of this bar



... which means we have used
50 + 34 %
or
84 %
of our fatigue life

This approach to trying to combine fatigue models at different stresses is called **Miner's Rule**. Note that this is called 'rule' because it is an unproven hypothesis.

$$C = \sum_{i=1}^k \frac{n_i}{N_i}$$

... the number of different stress levels → k

... the number of cycles at a particular stress level → n_i

... the fatigue limit for a particular stress level → N_i

... and we typically assume that failure will occur when $C = 1$ or 100 %

... but this figure is sometimes believed to be between 70 and 220 %

the RELIABILITY MINDSET.

We can make our life much easier if we try and think about **reliability life modes**. If we do, we can not only understand **reliability** better, but understand what it takes to make things **reliable**. And if we know how our things might fail, we don't waste time 'fixing' things that don't matter. And it also means that we can make better decisions ... like when to replace brake pads!

